Customer Channel Migration

Inaugural-Dissertation zur Erlangung des Doktorgrades des Fachbereichs Wirtschaftswissenschaften der Johann Wolfgang Goethe-Universität Frankfurt am Main

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Würzburg

2006

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1 Einleitung

Der Vertrieb von Produkten und Diensleistungen hat in den letzten Jahren einen immensen Strukturwandel erlebt. Unternehmen nutzen vermehrt den Direktvertrieb, um den bestehenden stationären Vertrieb zu ergänzen (May & Greyser 1989; Alba et al. 1997; Geyskens, Gielens, & Dekimpe 2002; Schoenbachler & Goeffrey 2002). Einer Studie der Aberdeen Group zufolge besitzen bereits 45 Prozent aller Unternehmen drei oder mehr Vertriebswege, um mit ihren Kunden zu interagieren (Shankar & Winer 2005).

Ausgelöst wurde diese Entwicklung von dem Ziel, durch eine vermehrte Implementierung direkter Vertriebswege die Kosten zu senken, die Umsätze zu steigern und die Kundenbindungsraten zu erhöhen (Prasad & Harker 2000; Anderson & Lanen 2002; Hitt & Frei 2002; Hoffman 2002).

Die Zielsetzung, durch den vermehrten Einsatz direkter Vertriebswege die Kosten zu senken, fußt auf der Annahme, kostenintensive Transaktionen auf kostengünstige direkte Vertriebswege transferieren zu können (Myers, Pickersgill, & Van Metre 2004). Zur Zeit nutzt der Großteil der Kunden den dezentral organisierten stationären Vertrieb, um mit den Unternehmen zu interagieren. Eine vermehrte Nutzung zentral organisierter Vertriebswege, wie dem Internet oder dem Call Center, könnten die Ressourcen der Unternehmen effizienter einsetzen und eine verstärkte Prozessautomatisierung ermöglichen (Kumar & Venkatesan 2005). Somit dürften die Kosten pro Interaktion im direkten Vertrieb deutlich unter den Kosten des stationären Vertriebs liegen (Booz Allen & Hamilton 1996). Ein Transfer kostenintensiver Transaktionen von dem stationären Vertrieb auf kostengünstigere Vertriebswege könnte somit die Gesamtkosten des Vertriebs senken.

Die Bestrebung, durch den vermehrten Einsatz von direkten Vertriebswegen eine Umsatzsteigerung zu erzielen, basiert auf der Annahme, durch ein breites Angebot an Vertriebswegen die Bedürfnisse der Kunden besser zu bedienen (Myers, Pickersgill, & Van Metre 2004). Diese gestiegene Kundenorientierung soll Kunden dazu motivieren, deren Nachfrage auf ein Unternehmen zu konsolidieren und somit zu einer Umsatzsteigerung beizutragen (Campbell 2003). Des weiteren wird häufig argumentiert, dass sich über direkte Vertriebswege für Unternehmen eine Vielzahl neuer Wege ergibt, um bisher unerreichte Kundensegmente zu erschließen.

Weiterhin verfolgen Unternehmen eine Strategie des vermehrten Einsatzes von direkten Vertriebswegen mit dem Ziel, die Kundenbindung zu steigern. Es besteht Grund zu der Annahme, dass sich Kunden an die Nutzung von direkten Vertriebeswegen gewöhnen. Haben sich Kunden einmal an die Nutzung eines Vertriebsweges gewöhnt, steigen somit die Kosten für einen Wechsel zum Wettbewerb (Chen & Hitt 2002). Dies liegt darin begründet, dass Kunden erneut die Nutzung des Vertriebsweges bei dem Wettbewerber erlernen müssten.

Trotz der anhaltenden Investitionen in den Direktvertrieb, gelingt es vielen Unternehmen bis zum heutigen Zeitpunkt jedoch nicht, die angestrebten Ziele zu erreichen (Myers, Pickersgill, & Van Metre 2004; Van Baal & Dach 2005). Stattdessen sind viele Unternehmen mit steigenden Kosten, sinkenden Umsätzen und abnehmenden Kundenbindungsraten konfrontiert.

Paradoxerweise werden die vermehrten Kosten durch jene Vertriebswege verursacht, die zu einer Kostenreduktion führen sollten. Zahlreiche Unternehmen bieten ihren Kunden eine Vielzahl an Vertriebswegen an, um mit ihnen zu interagieren (Ansari, Mela, & Neslin 2005). Kunden nutzen diese Freiheit und wählen die passenden Vertriebswege für ihre Bedürfnisse (Rangaswamy & Van Bruggen 2005). Diese Vertriebswegewahl entspricht jedoch oft nicht der optimalen Vertriebswegewahl aus Sicht des Unternehmens (Black et al. 2002). So kann es oft dazu kommen, dass Kunden nur einen geringen Prozentsatz ihrer kostenintensiven Transaktionen durch kostengünstige Transaktionen substituieren. Diese beschränkten Kosteneinsparungen werden jedoch durch die notwendigen Investitionen in die zusätzliche Infrastruktur und durch die Betriebskosten der neu geschaffenen Vertriebswege aufgewogen (Hitt, Frei, & Harker 1999; Hobmeier 2001). In Summe führt die Implementierung von zusätzlichen Vertriebswegen somit häufig zu einer Kostensteigerung anstatt zu einer Kostensenkung.

In ähnlicher Weise erfahren viele Unternehmen sinkende Umsätze, obwohl sie sich durch die Einführung direkter Vertriebswege eine Umsatzsteigerung erhofft haben. Einen Grund dafür stellt das Phänomen des „Free Riding“ dar (Van Baal & Dach 2005). Free Riding bezeichnet die Nutzung von Services in hochpreisigen Vertriebswegen, während der eigentliche Kauf durch den Kunden in einem niedrigpreisigen Vertriebsweg abgewickelt wird (Brynjolfsson & Smith 2000). Free Rider nehmen somit Leistungen in Anspruch, für die sie bei dem anschließenden Produktkauf nicht den entsprechenden Mehrwert bezahlen. Free Riding führt somit zu einem gestiegenen Druck auf die Margen der bestehenden Vertriebswege und zu einer allgemeinen Deflation der Preise. Dies führt wiederum zu sinkenden Umsätzen (Geyskens, Gielens, & Dekimpe 2002; Abele, Caesar, & John 2003; Van Baal & Dach 2005).

Abschließend ist anzuführen, dass Unternehmen auch nicht in der Lage waren, durch den vermehrten Einsatz von direkten Vertriebswegen Kunden stärker an das Unternehmen zu binden. Stattdessen hat sich gezeigt, dass Kunden die neuen Möglichkeiten des Direktvertriebs nutzen, um das für sie beste Angebot zu finden (Lynch & Ariely 2000; Campbell 2003). Dies liegt primär darin begründet, dass viele Unternehmen nicht in der Lage waren, die nötigen Wechselkosten oder den gewünschten Mehrwert für die Kunden zu schaffen.

Viele Unternehmen konnten die anvisierten Ziele nicht erreichen, weil sie der Entwicklung geeigneter Vertriebsstrategien zu wenig Aufmerksamkeit entgegengebracht haben. Allzu häufig wurden neue Vertriebswege unbedacht in eine vorhandene Vertriebswegestruktur eingeflochten (Myers, Pickersgill, & Van Metre 2004). Heutzutage ist es von Bedeutung, nicht nur einzelne Vertriebswege individuell zu managen, sondern ein breites Verständnis dafür zu entwickeln, wie Kundenbedürfnisse durch ein strategisch geplantes Distributionssystem profitabel erfüllt werden können. Viele Unternehmen aus den unterschiedlichsten Branchen haben es versäumt, daran zu denken, dass der Erfolg eines Vertriebsweges in erster Linie von der Nutzung durch die Kunden abhängt (Hobmeier 2001).

Customer Channel Migration ist eine Möglichkeit, diese Ziele dennoch zu erreichen. Customer Channel Migration bezeichnet die gezielte Steuerung des Vertriebswegenutzungsverhaltens von Kunden mit dem Ziel, die Kundenprofitabilität und Kundenbindung zu steigern (Myers, Pickersgill, & Van Metre 2004).

Studien zeigen zum Beispiel, dass eine integrierte Multikanalstrategie den Umsatzbeitrag des Distributionssystems um bis zu 50% erhöhen kann (Myers, Pickersgill, & Van Metre 2004). Die Bedeutung von Customer Channel Migration wird des weiteren dadurch bestätigt, dass das Thema „Managing and maintaining customers through multiple channels" zu den Top-Priorities des Marketing Science Instituts gezählt wird (Marketing Science Institute 2006). Trotz der immensen Bedeutung haben sich jedoch erst wenige Forscher mit diesem Thema auseinandergesetzt (Ansari, Mela, & Neslin 2005).

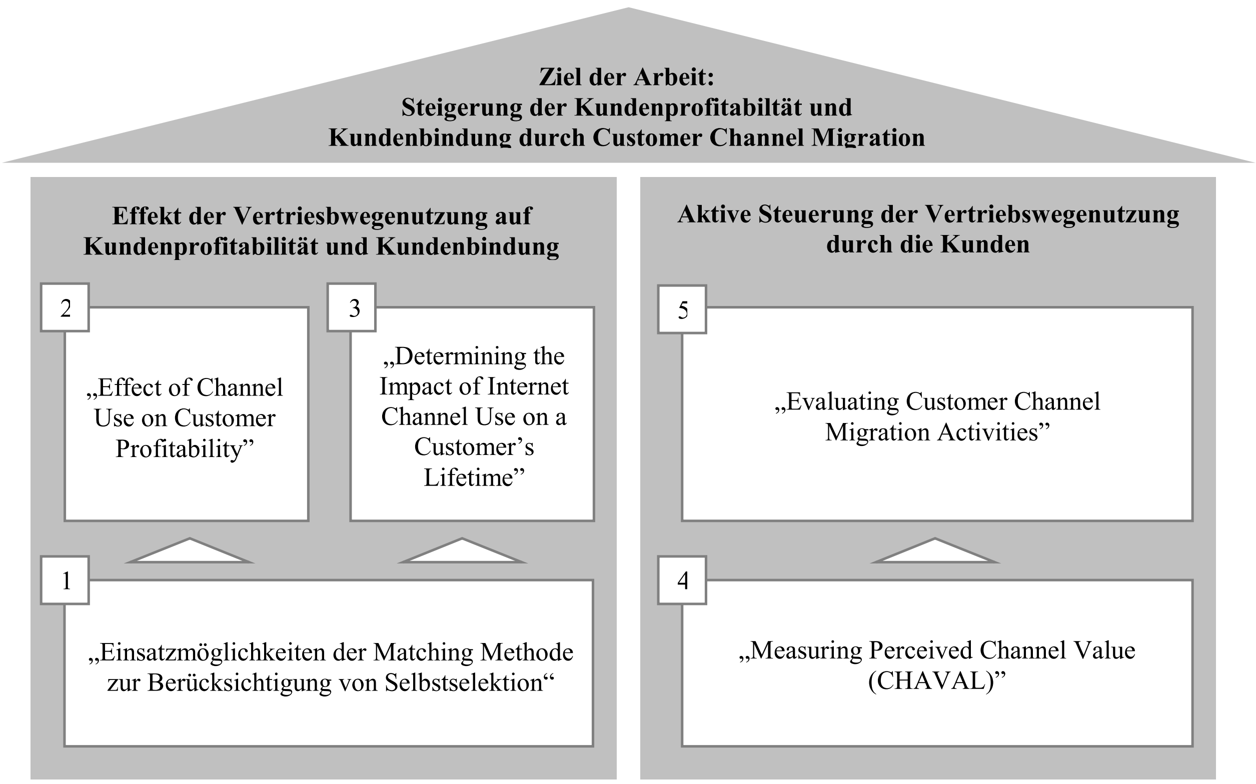
Ziel dieser Dissertation ist es daher, die Kundenprofitabilität und die Kundenbindung eines Unternehmens durch die aktive Steuerung des Vertriebswegenutzungsverhaltens zu steigern. Somit beschäftigt sich die Dissertation mit der Beantwortung zwei konkreter Fragestellungen:

I. Zum einen wird beantwortet, welche monetären und kundenbindenden Implikationen aus der Nutzung verschiedener Vertriebswege entstehen.

II. Zum anderen wird die Frage untersucht, wie die Vertriebswegenutzung von Kunden aktiv durch eine Unternehmen gesteuert werden kann.

Die vorliegende, kumulative Dissertation besteht aus insgesamt fünf aufeinander aufbauenden Beiträgen, die auf das übergreifende Ziel der Dissertation ausgerichtet sind. Die ersten drei Beiträge erarbeiten Antworten darauf, wie sich die Vertriebswegenutzung auf die Kundenprofitabilität und die Kundenbindung auswirkt. Die Beiträge vier und fünf beschäftigen sich hingegen damit, wie Kunden zwischen verschiedenen Vertriebswegen aktiv migriert werden können. Der Zusammenhang zwischen den fünf eben genannten Beiträgen ist in Abbildung 1 dargestellt. Im folgenden wird der Inhalt der Beiträge kurz skizziert und dargestellt, wie die Beiträge aufeinander aufbauen.

Abbildung 1 Überblick über die Dissertation



Häufig ist es in empirischen Studien von Interesse, den Effekt einer Maßnahme auf eine Ergebnisvariable zu untersuchen. Ein Beispiel für einen solchen Zusammenhang wäre der Einfluss der Vertriebswegenutzung auf die Kundenprofitabilität oder die Kundenbindung. Um jedoch eine unverzerrte Schätzung der Profitabilitäts- und Kundenbindungswirkung von Vertriebswegen zu erreichen, müssen Selbstselektionseffekte berücksichtigt werden.

Zu deren Ermittlung schlägt der erste Beitrag, „Einsatzmöglichkeiten der Matching Methode zur Berücksichtigung von Selbstselektion“, die Matching Methode vor. Bei der Matching Methode besteht das Ziel darin, durch die Bildung von Paaren aus Teilnehmern und Nicht-Teilnehmern den Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu bewerten. Dieser Beitrag stellt unterschiedliche Varianten der Matching Methode vor und vergleicht diese. Der Beitrag zeigt damit, wie bei betriebswirtschaftlichen Problemen Selbstselektionseffekte angemessen berücksichtigt werden können.

Der zweite und der dritte Beitrag wenden die Matching Methode auf konkrete Fragestellungen des Marketing an und untersuchen die Auswirkungen der Vertriebswegenutzung auf die Kundenprofitabilität und die Kundenbindung. Dabei beschäftigt sich der zweite Beitrag, „Effect of Channel Use on Customer Profitability“, mit der Frage, wie sich die Nutzung des Internets auf die Profitabilität von Kunden auswirkt. Die Ergebnisse einer umfangreichen empirischen Studie, die auf dem Datensatz einer großen europäischen Retailbank beruhen, bestätigen einen Effekt der Vertriebswegenutzung auf die Profitabilität eines Kunden.

Der dritte Beitrag, „Determining the Impact of Internet Channel Use on a Customer’s Lifetime”, bestimmt analog zum zweiten Beitrag die kundenbindende Auswirkung der Internetnutzung. Die Ergebnisse einer Studie, die wiederum die Daten einer großen europäischen Retailbank verwenden, finden einen positiven Effekt der Internetnutzung auf die Bindung eines Kunden an das Unternehmen.

Die Beiträge eins bis drei behandeln somit die Fragestellung, wie sich die Vertriebswegenutzung auf die Profitabilität und die Bindung von Kunden auswirkt. Der vierte und fünfte Beitrag der Dissertation untersuchen die gezielte Steuerung der Vertriebswegenutzung von Kunden in der Finanzdienstleistungsbranche.

Dabei entwickelt der vierte Beitrag, „Measuring Perceived Channel Value (CHAVAL)“, eine Skala zur Messung des wahrgenommenen Nutzens von Vertriebswegen durch Kunden. Der Beitrag entwickelt diese Skala anhand zweier Datensätze, die jeweils circa 500 Teilnehmer umfassen. Die finale Skala demonstriert, dass der wahrgenommene Nutzen eines Vertriebsweges aus drei Dimensionen besteht – dem Nutzen des Vertriebsweges in der Informationsphase, in der Kaufphase, und der Transaktionsphase. Jede dieser Dimensionen besteht wiederum aus mehreren Komponenten, die den Nutzen eines Vertriebsweges in einer Phase bestimmen.

Der fünfte Beitrag, „Evaluating Customer Channel Migration Activities“, baut auf den Erkenntnissen des vierten Beitrags auf und entwickelt ein Modell zur Erklärung des Vertriebswegewahlverhaltens von Kunden. Mit diesem Modell wird es ermöglicht, den Einfluss von Kundenmigrationsmaßnahmen auf die Vertriebswegenutzung und die damit verbundenen monetären Implikationen zu bestimmen. Die Ergebnisse einer empirischen Studie, die auf der Befragung von 500 Bankkunden basiert, identifizieren die wahrgenommene Qualität und Convenience als die zwei bedeutendsten Faktoren, die die Vertriebswegenutzung eines Kunden beeinflussen.

Zusammenfassend kann somit festgehalten werden, dass Customer Channel Migration in der Lage ist, die langfristige Profitabilität eines Unternehmens zu steigern. Die Ergebnisse der Dissertation deuten darauf hin, dass sich Customer Channel Migration eignet, die Kundenprofitabilität und die Kundenbindung zu steigern. Darüber hinaus bietet die Dissertation konkrete Aussagen, wie Kunden zwischen verschiedenen Vertriebswegen migriert werden können, um die prognostizierten Ergebnisse zu erzielen. Der wissenschaftliche und der inhaltliche Mehrwert der Beiträge wird in der Tabelle 1 kurz zusammengefasst.

Tabelle 1 Zusammenfassung des wissenschaftlichen und inhaltlichen Beitrags

Beitrag	Titel	Wissenschaftlicher Beitrag	Inhaltlicher Beitrag
1	„Einsatzmöglichkeiten der Matching Methode zur Berücksichtigung von Selbstselektion“	Darstellung des Selbstselektionsproblems und Einführung der Matching Methode ins Marketing	Anwendungsorientierte Darstellung der Matching Methode
2	„Effect of Channel Use on Customer Profitability”	Überprüfung der Eignung der Matching Methode zur Bestimmung unverzerrter Effekte	Effekt der Internetnutzung auf die Kundenprofitabilität
3	„Determining the Impact of Internet Channel Use on a Customer’s Lifetime”	Entwicklung eines Ansatzes zur Berücksichtigung von Selbstselektion und Rechtszensierung	Effekt der Internetnutzung auf die Kundenbindung
4	„Measuring Perceived Channel Value (CHAVAL)”	Skala zur Messung des wahrgenommenen Nutzens eines Vertriebsweges	Identifikation der Faktoren, die für das Vertriebswegedesign relevant sind
5	„Evaluating Customer Channel Migration Activities”	Modell zur Beschreibung des Vertriebswegewahlverhaltens und zur Prognose der Vertriebswegenutzung	Identifikation der relevanten Migrationsmaßnahmen und deren Wirkung auf die Vertriebswegenutzung

2 Detaillierte Darstellung der Beiträge

2.1 Beitrag 1 – Einsatzmöglichkeiten der Matching Methode zur Berücksichtigung von Selbstselektion

Häufig ist es von Interesse, den Effekt einer Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu untersuchen. Hierzu zählen zum Beispiel folgende Fragestellungen: Hat die Nutzung eines bestimmten Vertriebsweges einen Einfluss auf die Profitabilität eines Kunden? Wirkt sich die Vertriebswegenutzung eines Kunden auf dessen Bindung an ein Unternehmen aus?

Bei diesen Fragestellungen gilt es, einen kausalen Zusammenhang zwischen einer Maßnahme (Vertriebswegenutzung) und einer Ergebnisvariablen (Kundenprofitabilität oder Kundenbindung) zu untersuchen. Um jedoch eine Kausalität adäquat evaluieren zu können, ist es nicht ausreichend, den Mittelwertunterschied einer Ergebnisvariablen zwischen der Gruppe der Teilnehmer und der Nicht-Teilnehmer an einer Maßnahme zu berechnen. Denn häufig ist die Zuordnung eines Probanden zu einer Gruppe (Teilnehmer versus Nicht-Teilnehmer an der Maßnahme) nicht zufällig, sondern die Probanden ordnen sich einer Gruppe selbst zu (Selbstselektionseffekt). In solchen Fällen kann dieser Mittelwertunterschied nicht der Teilnahme an einer Maßnahme zugeschrieben werden, da der beobachtete Unterschied sowohl durch den Effekt der Teilnahme an der Maßnahme als auch durch einen Selbstselektionseffekt bedingt sein kann.

Häufig wird jedoch in der Unternehmenspraxis bereits Kausalität unterstellt, wenn ein Mittelwertvergleich Unterschiede zwischen zwei Gruppen aufdeckt. So wurde bei Untersuchungen, die den Einfluss der Vertriebswegenutzung auf die Kundenprofitabilität zu bestimmen versuchten, ein positiver Einfluss der Internetnutzung auf die Kundenprofitabilität unterstellt, da ein Mittelwertvergleich signifikante Unterschiede zwischen Internetnutzern und Nicht-Internetnutzern gezeigt hat (Essayan, Rutstein, & Wetenhall 2002; Wehrling 2002). Diese Studien vernachlässigen jedoch, dass sich Internetnutzer von Kunden, die das Internet nicht nutzen, signifikant unterscheiden. Es liegt demnach ein Selbstselektionseffekt vor (Degeratu, Rangaswamy, & Wu 2000) und es ist nicht möglich, die höhere Profitabilität von Kunden, die das Internet nutzen, gänzlich auf die Internetnutzung zurückzuführen.

Zur Berücksichtigung des Selbstselektionseffekts wird in der Medizin (z. B. Singer 1986; D'Agostino 1998) und der Volkswirtschaftslehre (z. B. LaLonde 1986; Heckman et al. 1996; Ashenfelter & Rouse 1998) die so genannte Matching Methode als ein nicht parametrisches

Verfahren vorgeschlagen. Diese Methode hat jedoch in der Betriebswirtschaftslehre bislang kaum Beachtung gefunden.

Aus diesem Grund ist es das Ziel dieses Beitrags, aufzuzeigen, wie Selbstselektionseffekte berücksichtigt werden können, um eine adäquate Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu gewährleisten. Hierfür wird die Matching Methode dargestellt. Bei der Darstellung der Matching Methode besteht das Ziel darin, den Einfluss unterschiedlicher Varianten bei der Anwendung der Matching Methode auf die Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable aufzuzeigen. Die Grundidee der Matching Methode besteht darin, systematische Unterschiede zwischen der Gruppe der Teilnehmer und der Nicht-Teilnehmer an einer Maßnahme zu eliminieren (Heckman et al. 1996). So kann die nicht-zufällige Zuordnung der Probanden zu den Gruppen beseitigt und das Design einer experimentellen Untersuchung nachgebildet werden. Um dieses Ziel zu erreichen, werden „Zwillingspaare“ aus der Gruppe der Teilnehmer und Nicht-Teilnehmer gebildet, die sich nur bezüglich des Teilnahmestatus unterscheiden (Hujer, Caliendo, & Radic 2003, S. 18). Somit werden jedem Teilnehmer ein oder mehrere Nicht-Teilnehmer als Matching-Partner zugeordnet. Auf Basis der ermittelten Matching-Partner kann dann der Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable evaluiert werden.

Der wissenschaftliche Beitrag jener Arbeit liegt in der Sensibilisierung für das Problem der Selbstselektion und darüber hinaus in der anwendungsorientierten Darstellung der Matching Methode zur Berücksichtigung von Selbstselektionseffekten.

2.2 Beitrag 2 – Effect of Channel Use on Customer Profitability

Retailbanken setzen zahlreiche Vertriebskanäle ein, um die Beziehung zu den Kunden zu gestalten. Im Besonderen kommt dabei dem Internet als Vertriebsweg eine große Bedeutung zu. Dies resultiert vor allem daraus, dass sich Retailbanken Umsatzsteigerungen und Kosteneinsparungen durch den verstärkten Einsatz des Internets versprechen.

In jüngster Zeit finden sich jedoch widersprüchliche Aussagen hinsichtlich des Effekts der Internetnutzung durch die Kunden auf deren Profitabilität (Rasch & Lintner 2001; Wehrling 2002). Aus diesem Grund ist eine empirische Untersuchung dieses Zusammenhangs anzuraten.

Um die Vorteilhaftigkeit eines Vertriebsweges beurteilen zu können, ist die Ermittlung des Effekts der Vertriebswegenutzung auf die Profitabilität der Kunden entscheidend. Die

Ermittlung dieses Effekts ist mit Hilfe eines einfachen Mittelwertvergleichs jedoch nicht möglich, da sich Kunden selbst entscheiden, ob sie einen Vertriebsweg nutzen wollen (Hitt & Frei 2002). Dies kann dazu führen, dass sich die Gruppe der Kunden, die einen bestimmten Vertriebsweg nutzt, und die Gruppe jener Kunden, die diesen Vertriebsweg nicht nutzt, in ihrer Struktur systematisch unterscheiden. Somit können neben dem Kanaleffekt, also dem Effekt der Nutzung des Vertriebsweges auf die Profitabilität, erhebliche Selbstselektionseffekte vorliegen.

Ziel des Beitrags ist es daher, den unverzerrten Effekt der Internetnutzung auf die Profitabilität eines Bankkunden mit Hilfe der Matching Methode zu bestimmen. Zudem wird im Rahmen einer empirischen Studie gezeigt, dass die Berücksichtigung von Selbstselektionseffekten für eine Ermittlung des Effekts der Internetnutzung auf die Profitabilität von Bankkunden relevant ist.

Die Ergebnisse der empirischen Studie demonstrieren, dass Internetnutzung einen positiven Effekt auf die Profitabilität von Bankkunden hat. Darüber hinaus zeigt die empirische Studie, dass die Berücksichtigung von Selbstselektionseffekten notwendig ist, um verzerrte Ergebnisse zu vermeiden. So wird zum Beispiel der Effekt der Internetnutzung auf die Kundenprofitabilität überschätzt, wenn lediglich ein Mittelwertvergleich der Profitabilität von Internetnutzern und Kunden, die nicht das Internet nutzen, erfolgt. Hinsichtlich der Ableitung einer Strategie für das Kundenmanagement ergibt sich, dass eine Migration der Nutzer „traditioneller" Vertriebswege zum Internet zweckmäßig ist.

Der Beitrag dieses Aufsatzes zur bisherigen Forschung besteht darin, dass der Effekt der Internetnutzung auf die Profitabilität von Bankkunden unverzerrt ermittelt wird, die Matching Methode als geeignetes Verfahren diskutiert und angewendet wird und Implikationen für Retailbanken bezüglich einer Strategie für die Migration der Kunden abgeleitet werden.

2.3 Beitrag 3 – Determining the Impact of Internet Use on a Customer's Lifetime

Der Markt für Finanzdienstleistungen unterliegt seit einigen Jahren einem tief greifenden Strukturwandel (Hitt, Frei, & Harker 1999). Stagnierende Märkte und zunehmender Konkurrenzdruck führen dazu, dass dem effizienten Umgang mit dem Kunden eine immer größere Bedeutung zukommt (Webster 1992). Durch den Paradigmenwechsel im Marketing, der eine Refokussierung von einer reinen transaktionsbasierten Strategie zugunsten einer kundenorientierten Strategie bewirkt hat, gewinnen Erkenntnisse zu einem besseren Verständnis der Kundenbindung sowie Aktivitäten zur Sicherung bestehender Kundenbeziehungen zunehmend an Bedeutung (Blattberg & Deighton 1996). Ausgelöst wurde dieser Paradigmenwechsel durch empirische Untersuchungen, die zeigen konnten, dass bereits eine 5%-ige Steigerung der Kundenbindungsrate den Gewinn einer Unternehmung um bis zu 85% erhöhen kann (Reichheld & Sasser 1990). In Anbetracht dessen fassen Banken die Kundenbindung nicht mehr nur als Aufgabe einer funktionalen Einheit auf, sondern verstehen sie als zentrale Herausforderung für ihren zukünftige Erfolg.

Damit einhergehend hat die Diffusion neuer Vertriebswege, wie zum Beispiel des Internets, den Vertrieb von Finanzdienstleistungen revolutioniert. Aus Bankensicht ergeben sich hieraus vor allem Kosteneinsparungen bei Standardleistungen aufgrund des hohen Grades an Prozessautomation. Die Kostenvorteile und die dadurch initiierte Begeisterung für elektronische Vertriebskanäle sind jedoch bei zahlreichen Banken rasch der ernüchternden Erkenntnis gewichen, dass parallel zu den Rationalisierungsvorteilen der nachlassende Kundenkontakt sowie das riesige Spektrum an Informations- und Vergleichsmöglichkeiten die Langfristorientierung der Kunde-Bank-Beziehung gefährden kann (Reitsma et al. 2004; Schaaf 2005). Vor diesem Hintergrund wirft sich für die Bank die Frage auf, inwieweit die Internetnutzung die Kundenbindung und damit die langfristige Profitabilität der Bank beeinflusst.

Die Untersuchung des Einflusses der Internetnutzung auf die Kundenbindung ist in den letzten Jahren ein wesentliches Thema wissenschaftlicher Arbeiten gewesen. Jedoch weisen die bestehenden Beiträge Schwächen auf, die eine unverzerrte Schätzung des Effekts der Internetnutzung auf die Kundenbindung verhindern. So findet sich kein Beitrag in der bestehenden Literatur, der für das Problem der Selbstselektion und gleichzeitig für das Problem der Rechtszensierung Rechnung trägt. Eine Berücksichtigung der Selbstselektion und Rechtszensierung ist jedoch notwendig, um eine unverzerrte Schätzung des Effekts der Internetnutzung auf die Kundenbindung zu ermöglichen.

Ziel dieses Beitrags ist es daher, den unverzerrten Effekt der Internetnutzung auf die Kundenbindung zu bestimmen und basierend auf den Ergebnissen strategische Implikationen für die Kundenmigration abzuleiten. Um eine unverzerrte Schätzung dieses Effekts zu ermöglichen, kommt eine Kombination aus der Matching Methode und eines Hazard Modells zur Anwendung.

Die Ergebnisse einer empirischen Untersuchung ergeben, dass Internetnutzung einen positiven Effekt auf die Bindung von Bankkunden hat. Es zeigt sich, dass die Wahrscheinlichkeit einer Abwanderung des Kunden durch die Nutzung des Internets um 88 Prozent gesenkt werden kann. Aus diesem Ergebnis können interessante Schlussfolgerungen für die Gestaltung von Migrationsstrategien abgeleitet werden. So weisen die Ergebnisse darauf hin, dass durch die gezielte Migration zum Internet die durchschnittliche Kundenbindungsrate gesteigert werden kann.

Der Beitrag dieses Aufsatzes zur bisherigen Forschung besteht darin, dass der Effekt der Internetnutzung auf die Kundenbindung unverzerrt ermittelt wird. Dies wird erreicht, indem eine Kombination zweier statistischer Verfahren – der Matching Methode und eines Hazard Modells – angewendet wird, um das Problem der Selbstselektion und der Rechtszensierung zu berücksichtigen. Des weiteren wird ein Beitrag geleistet, indem strategische Implikationen für die Migration von Bankkunden aus den vorliegenden Ergebnissen abgeleitet werden.

2.4 Beitrag 4 – Measuring Perceived Channel Value

Nachdem der Effekt der Internetnutzung auf die Kundenprofitabilität und die Kundenbindung bestimmt wurde und in beiden Fällen ein positiver Effekt gefunden wurde, stellt sich nun die Frage, wie Kunden zu einer vermehrten Nutzung des Internets bewegt werden können. Dies soll nun in den beiden folgenden Beiträgen näher untersucht werden.

Die Unternehmen haben erkannt, dass das Vertriebswegeangebot als ein wichtiger Faktor zur Differenzierung gegenüber dem Wettbewerb dienen kann. Somit ist es vorteilhaft, die Vertriebswege auf die Bedürfnisse der Kunden abzustimmen. Aus diesem Grund bieten zahlreiche Unternehmen ihren Kunden ein breites Angebot an Vertriebswegen an (Ansari, Mela, & Neslin 2005). Die Unternehmen erhoffen sich dadurch, dass die Kunden den für sie passenden Vertriebsweg in dieser breiten Auswahl finden. Ein Grund für dieses Vorgehen liegt darin, dass Unternehmen bisweilen nicht in der Lage sind, den Nutzen eines Vertriebsweges für den Kunden zu messen (Levy 1999). Um das Vertriebswegeangebot besser auf die Bedürfnisse der Kunden abzustimmen, wäre es vorteilhaft, den wahrgenommen Nutzen eines Vertriebsweges durch die Kunden zu messen. Dies würde es ermöglichen, das Vertriebswegedesign und das Vertriebswegemanagement effizienter zu gestalten.

Trotz der großen Bedeutung dieses Themas ist die Forschung auf diesem Gebiet noch sehr beschränkt. Die bestehende Literatur weist keinen Beitrag auf, der eine Skala zur Messung des wahrgenommenen Nutzens eines Vertriebsweges entwickelt (Forsythe et al. 2006).

Ziel dieses Beitrags ist es daher, eine Skala zur Messung des wahrgenommenen Nutzens eines Vertriebsweges zu entwickeln und zu evaluieren.

Die Ergebnisse einer empirischen Untersuchung zeigen, dass sich der Nutzen eines Vertriebsweges, den ein Kunde wahrnimmt, aus drei Dimensionen zusammensetzt: aus dem Nutzen, den ein Vertriebsweg in der Informationsphase, in der Kaufphase und der Transaktionsphase des Kaufprozesses stiftet (Gradial et al. 1994). Jede dieser Dimensionen besteht wiederum aus verschiedenen Komponenten, die den Nutzen eines Vertriebswegs einer bestimmten Phase des Kaufprozesses bestimmen. Diese umfassen die wahrgenommene Qualität, die Convenience, das Risiko und die Kosten, die mit der Nutzung eines Vertriebsweges verbunden sind. Die entwickelte Skala umfasst insgesamt 22 Items und konnte anhand von zwei unterschiedlichen Datensätzen bestätigt werden.

Der wissenschaftliche Mehrwert des Beitrags liegt in der Entwicklung einer Skala, die zur Messung des Vertriebswegenutzens verwendet werden kann. Somit schließt dieser Beitrag eine Lücke in der bestehenden Literatur und trägt zum weiteren Verständnis des Vertriebswegewahlverhaltens bei.

2.5 Beitrag 5 – Evaluating Customer Channel Migration Activities

Der zweite und der dritte Beitrag dieser Dissertation konnten bereits zeigen, dass es aus Sicht eines Unternehmens sinnvoll ist, die Vertriebswegenutzung von Kunden aktiv zu beeinflussen.

Die aktive Beeinflussung der Vertriebswegenutzung von Kunden setzt jedoch ein Verständnis des Vertriebswegewahlverhaltens voraus (Thomas & Sullivan 2005). Nur so ist es möglich, Strategien für die Kanalmigration zu entwickeln, die die Vertriebswegenutzung der Kunden gezielt beeinflussen.

Die Literatur zeigt, dass ein Kunde jenen Vertriebsweg wählt, der ihm in einer spezifischen Situation den höchsten Nutzen stiftet (Sweeney 2001). Um das Vertriebswegewahlverhalten der Kunden aktiv zu beeinflussen, ist es somit zunächst erforderlich, jene Faktoren zu ermitteln, die den wahrgenommenen Nutzen eines Vertriebsweges determinieren (Montoya-Weiss, Voss, & Grewal 2003). Anschließend kann – aufbauend auf diesen Erkenntnissen – das Vertriebswegewahlverhalten modelliert werden. Dieses Modell wiederum kann verwendet werden, um die Wirkung von Migrationsmaßnahmen zu simulieren.

Ziel dieses Beitrags ist es, das Vertriebswegewahlverhalten von Kunden zu modellieren, um somit strategische Implikationen für die aktive Kanalmigration abzuleiten.

Der Beitrag ist in zwei Teile gegliedert, die aufeinander aufbauen. Dabei modelliert der erste Teil des Beitrags die Vertriebswegewahl der Kunden und identifiziert die relevanten Einflussfaktoren. Der zweite Teil des Beitrags baut auf dem entwickelten Vertriebswegewahlmodell auf und simuliert den Einfluss von Migrationsmaßnahmen auf die Vertriebswegenutzung und die Unternehmensprofitabilität.

Die Ergebnisse einer empirischen Untersuchung zeigen, dass die Vertriebswegewahl von Kunden insbesondere durch drei Faktoren beeinflusst wird: kundenspezifische, situationsspezifische und vertriebswegespezifische Faktoren. Insbesondere den vertriebswegespezifischen Faktoren kommt der entscheidende Einfluss bei der Vertriebswegewahl zu. Diese vertriebswegespezifischen Faktoren stellen den wahrgenommenen Nutzen eines Vertriebsweges dar, der mit Hilfe der in Beitrag vier erstellten Skala erhoben werden kann.

Der zweite Teile des Beitrags nutzt nun das entwickelte Vertriebswegewahlmodell und eine Simulation, um den Einfluss verschiedener Aktivitäten der Kanalmigration zu bestimmen. Hier zeigt sich, dass eine Kanalmigration insbesondere gefördert werden kann, indem die wahrgenommene Convenience und Qualität eines Vertriebsweges verbessert wird. Eine anschließende Simulation der monetären Auswirkungen dieser Migrationsmaßnahmen zeigt, dass die Unternehmensprofitabilität durch die Kanalmigration signifikant gesteigert werden kann.

Dennoch sind heute noch viele Retailbanken zurückhaltend, das Kanalnutzungsverhalten ihrer Kunden aktiv zu beeinflussen. Dies wird häufig durch die negativen Erfahrungen deutscher Banken begründet, die eine Kanalmigration ihrer Kunden zu erzwingen suchten. Die vorgeschlagene Vorgehensweise propagiert aber keine erzwungene Kanalmigration, sondern setzt bei der Gestaltung der Vertriebswege gemäß den Präferenzen der Kunden an und ist somit kundenorientiert.

Der Beitrag dieses Aufsatzes liegt insbesondere in der Modellierung des Vertriebswegewahlverhaltens. Die bestehende Literatur bietet bis jetzt nur theoretische Ansätze und hat es bisher versäumt, diese empirisch abzubilden. Des weiteren leitet dieser Beitrag strategische Implikationen für die Kanalmigration ab, die mit Hilfe einer Simulation überprüft werden können.

3 Zusammenfassung

Jeder Beitrag der kumulativen Dissertation liefert Erkenntnisse zum Thema „Customer Channel Migration“. Die Dissertation bietet sowohl Akademikern als auch Praktikern einen Einblick, wie sich die Vertriebswegenutzung auf den Lebenswert eines Kunden auswirkt und wie diese Informationen genutzt werden können, um die langfristige Profitabilität eines Unternehmens zu steigern.

Aus einer akademischen Perspektive trägt die Arbeit in vielfacher Hinsicht zu der momentanen Forschung bei. Dabei sind insbesondere die Darstellung und die Anwendung der

Matching Methode hervorzuheben. Die Matching Methode ermöglicht es, Selbstselektionseffekte zu berücksichtigen und somit den unverzerrten Effekt einer Maßnahme auf eine Ergebnisvariable zu ermitteln. Obwohl sich viele Marketingprobleme mit einer solchen Situation auseinandersetzen, wird die Berücksichtigung von Selbstselektionseffekten fälschlicherweise vernachlässigt. Der zweite bedeutende Beitrag besteht in der Modellierung des Vertriebswegewahlverhaltens von Kunden und der Simulation der Auswirkung von Migrationsmaßnahmen auf die Vertriebswegenutzung.

Aus einer praxisorientierten Sicht ist festzuhalten, dass die Dissertation eine umfassende Anleitung bietet, um den durchschnittlichen Kundenwert mit Hilfe der Kanalmigration zu steigern. Einerseits werden Antworten darauf gegeben, welche Vertriebswege die Kundenprofitabilität und Kundenbindung positiv beeinflussen. Andererseits bietet die Dissertation eine Anleitung für die Gestaltung effizienter Strategien zur Kanalmigration.

4 Literatur

Abele, J., Caesar, W. K., & John, R. H. (2003). Rechanneling Sales. *McKinsey Quarterly*, 2-13.

Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentive to Participate in Electronic Marketplaces. *Journal of Marketing*, 61, 38-53.

Anderson, S., & Lanen, W. (2002). Using Electronic Data Interchange (EDI) to Improve the Efficiency of Accounting Transactions. *The Accounting Review*, 77, 703-730.

Ansari, A., Mela, C., & Neslin, S. (2005). *Customer Channel Migration*. Working Paper, Columbia University, New York.

Ashenfelter, O., & Rouse, C. (1998). Income, Schooling, and Ability: Evidence from a New Sample of Identical Twins. *The Quarterly Journal of Economics*, 253-284.

Black, N. J., Lockett, A., Ennew, C., Winklhofer, H., & McKechnie, S. (2002). Modelling Consumer Choice Of Distribution Channels: An Illustration from Financial Services. *International Journal of Bank Marketing*, 20, 161-173.

Blattberg, R. C., & Deighton, J. (1996). Managing Marketing by the Customer Equity Criterion. *Harvard Business Review*, 74, 136-44.

Booz Allen & Hamilton (1996). *Internet Banking: A Survey of Current and Future Development*. White Paper, New York: Financial Services Group.

Brynjolfsson, E., & Smith, M. D. (2000). Frictionless Commerce? A Comparison of Internet and Conventional Retailers. *Management Science*, 46, 563-585.

Campbell, D. (2003). *The Cost Structure and Customer Profitability Implications of Electronic Distribution Channels: Evidence from Online Banking*. Working Paper, Harvard Business School, Cambridge.

Chen, P.-Y., & Hitt, L. M. (2002). Measuring Switching Costs And The Determinants Of Customer Retention In Internet-enabled Businesses: A Study Of The Online Brokerage Industry. *Information Systems Research*, 13, 255-276.

D'Agostino, R. B. (1998). Tutorial in Biostatics: Propensity Score Methods for Bias Reduction in the Comparison of a Treatment to a Non-Randomized Control Group. *Statistics in Medicine*, 17, 2265-2281.

Degeratu, A., Rangaswamy, A., & Wu, J. (2000). Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes. *International Journal of Research in Marketing*, 17, 55-78.

Essayan, M., Rutstein, C., & Wetenhall, P. (2002). *Activate and Integrate: Optimizing the Value of Online Banking*. White Paper, Boston: The Boston Consulting Group.

Forsythe, S., Liu, C., Shannon, D., & Gardner, L. C. (2006). Development of a Scale to Measure the Perceived Benefits and Risks of Online Shopping. *Journal of Interactive Marketing*, 20, 55-75.

Geyskens, I., Gielens, K., & Dekimpe, M. G. (2002). The Marketing Valuation of Internet Channel Addition. *Journal of Marketing*, 66, 102-119.

Gradial, S., Clemons, S. D., Woodruff, R. B., Schumann, D. W., & Burns, M. J. (1994). Comparing Consumers' Recall of Prepurchase and Postpurchase Evaluation Experiences. *Journal of Consumer Research*, 20, 548-560.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1996). Sources of Selection Bias in Evaluating Social Programs: An Interpretation of Conventional Measures and Evidence on the Effectiveness of Matching as a Program Evaluation Method. *Proceedings of the National Academy of Science*, 93, 13416-13420.

Hitt, L. M., & Frei, F. X. (2002). Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking. *Management Science*, 48, 732-748.

Hitt, L. M., Frei, F. X., & Harker, P. (1999). How Financial Firms Decide on Technology. In R. E. Litan, & A. M. Santomero (Eds.), *Brookings Wharton Papers on Financial Services* (pp. 93-146). Washington: Brookings Institution.

Hobmeier, M. (2001). Professional Multichannel Management. *CEO*, 36-38.

Hoffman, K. (2002). Online Banking Aligns Practices: Now That The Initial Online Flurry Has Subsided, Web-based Banks Are Looking At ROI Potential. *Bank Technology News*, 26-29.

Hujer, R., Caliendo, M., & Radic, D. (2003). *Methods and Limitations of Evaluation and Impact Research*. Working Paper, Johann Wolfgang Goethe-University, Frankfurt.

Kumar, V., & Venkatesan, R. (2005). Who Are The Multichannel Shoppers And How Do They Perform?: Correlates Of Multichannel Shopping Behavior. *Journal of Interactive Marketing*, 19, 44-62.

LaLonde, R. J. (1986). Evaluating the Econometric Evaluations of Training Programs with Experimental Data. *The American Economic Review*, 76, 604-620.

Levy, M. (1999). Revolutionizing the Retail Pricing Game. *Discount Store News*, 38, 15.

Lynch, J. G., & Ariely, D. (2000). Wine Online: Search Costs Affect Competition an Price, Quality and Distribution. *Marketing Science*, 19, 83-103.

Marketing Science Institute (2006). *Research Priorities 2004-2006*. Retrieved 25th of June 2006, from http://www.msi.org/msi/rp0406.cfm#RP-CMC.

May, E. G., & Greyser, S. A. (1989). From Home-Shopping: Where Is It Leading? In L. Pellegrini, & S. K. Reddy (Eds.), *Retail and Marketing Channels - Economic and Marketing Perspectives on Producer-Distributor Relationships* (pp. 216-233). London: Routledge.

Montoya-Weiss, M. M., Voss, G. V., & Grewal, D. (2003). Determinants of Online Channel Use and Overall Satisfaction with a Relational, Multichannel Service Provider. *Journal of the Academy of Marketing Science*, 31, 448-458.

Myers, J., Pickersgill, A., & Van Metre, E. (2004). Steering Customers to the Right Channels. *McKinsey Quarterly*, 2004, 36-47.

Prasad, B., & Harker, P. (2000). *Pricing Online Banking Services Amid Network Externalities*. Paper presented at the 33rd Hawaii International Conference on System Sciences, Hawaii, USA.

Rangaswamy, A., & Van Bruggen, G. H. (2005). Opportunities and Challenges in Multichannel Marketing: An Introduction to the Special Issue. *Journal of Interactive Marketing*, 19, 5-11.

Rasch, S., & Lintner, A. (2001). *The Multichannel Consumer: The Need To Integrate Online and Offline Channels In Europe*. White Paper, Boston: Boston Consulting Group.

Reichheld, F., & Sasser, W. E. (1990). Zero Defections: Quality Comes to Services. *Harvard Business Review*, 68, 105-111.

Reitsma, R., Omwando, H. K., Jackson, P., & Herzog, C. (2004). *The 2004 European Online Retail Consumer*. White Paper, Cambridge: Forrester Research.

Schaaf, J. (2005). *E-Banking Snapshot*. White Paper, Frankfurt: Deutsche Bank Research.

Schoenbachler, D. D., & Goeffrey, G. L. (2002). Multi-Channel Shopping: Understanding What Drives Channel Choice. *Journal of Consumer Marketing*, 19, 42-53.

Shankar, V., & Winer, R. S. (2005). Interactive Marketing Goes Multichannel. *Journal of Interactive Marketing*, 19, 2-3.

Singer, B. (1986). Self-Selection and Performance-Based Ratings: A Case Study in Program Evaluation. In H. Wainer (Ed.), *Drawing Inference from Self-Selected Samples* (pp. 29-62).

Sweeney, J. (2001). Consumer Perceived Value: The Development of a Multiple Item Scale. *Journal of Retailing*, 77, 203-220.

Thomas, J. S., & Sullivan, U. Y. (2005). Managing Marketing Communications with Multichannel Customers. *Journal of Marketing*, 69, 239-251.

Van Baal, S., & Dach, C. (2005). Free Riding And Consumer Retention Across Retailers' Channels. *Journal of Interactive Marketing*, 19, 75-85.

Webster, F. E. (1992). The Changing Role of Marketing in the Corporation. *Journal of Marketing*, 56, 1-17.

Wehrling, R. (2002). Retail E-Banking: Tinkering Pays Off. *ABA Banking Journal*, 11-23.

Beitrag 1

Einsatzmöglichkeiten der Matching Methode zur Berücksichtigung von Selbstselektion

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Einsatzmöglichkeiten der Matching Methode zur Berücksichtigung von Selbstselektion

Abstrakt

Häufig ist es von Interesse, den Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu untersuchen. Um jedoch eine Kausalität adäquat evaluieren zu können, müssen Selbstselektionseffekte berücksichtigt werden. Hierfür wird die Matching Methode vorgeschlagen. Bei der Matching Methode besteht das Ziel darin, durch die Bildung von Paaren von Teilnehmern und Nicht-Teilnehmern den Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu bewerten. Dieser Beitrag stellt unterschiedliche Varianten der Matching Methode vor und vergleicht diese. Der Beitrag zeigt damit, wie bei betriebswirtschaftlichen Problemen Selbstselektionseffekte angemessen berücksichtigt werden können.

Keywords: Selbstselektion, Matching Methode, Kausalität

1 Einleitung

Häufig ist es von Interesse, den Effekt einer Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu untersuchen. So interessieren beispielsweise in der Volkswirtschaft und Politik folgende Fragestellungen: Verkürzt die Teilnahme an einer Arbeitsbeschaffungsmaßnahme die Dauer bis eine neue Beschäftigung erfolgt? Wirkt sich das Niveau der Schulbildung auf das spätere Einkommen aus? Aber auch in der Betriebswirtschaft finden sich zahlreiche Fragestellungen, die sich mit dem Effekt einer Teilnahme an einer Maßnahme auf eine Ergebnisvariable befassen. Hierzu zählen zum Beispiel folgende Fragestellungen: Wirkt sich der Besitz einer Kundenkarte positiv auf den Umsatz des Kunden aus? Hat die Nutzung eines bestimmten Vertriebswegs einen Einfluss auf die Profitabilität eines Kunden? Wie wirkt sich die Innovativität von Unternehmen auf deren Erfolg aus? Inwieweit beeinflusst die Nominierung für einen Academy Award den Erfolg eines Films an den Kinokassen? Welche Wirkung hat die Einführung eines Category Managements auf den Absatz eines Händlers?

Bei all jenen Fragestellungen gilt es, den Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable zu untersuchen, um einen kausalen Zusammenhang zu bestätigen oder zu verwerfen. Wenn eine Kausalität festgestellt werden kann, ergeben sich daraus Implikationen für die Politik oder Management-Entscheidungen. Um jedoch eine Kausalität adäquat evaluieren zu können, ist es von Bedeutung zwischen der Ermittlung und der Interpretation des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu trennen. Denn häufig ist die Zuordnung eines Probanden zu einer Gruppe (Teilnehmer versus Nicht-Teilnehmer an der Maßnahme) nicht zufällig, sondern die Probanden ordnen sich einer Gruppe selbst zu (Selbstselektionseffekt). In solchen Fällen kann ein Vergleich der beiden Gruppen Unterschiede zwischen diesen identifizieren, jedoch kann der Effekt der Teilnahme an einer Maßnahme auf die Ergebnisvariable dann nicht in einfacher Weise untersucht werden. Denn der beobachtete Unterschied zwischen den beiden Gruppen kann sowohl durch den Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable als auch durch weitere nicht berücksichtigte Variablen (Störvariablen), die einen Selbstselektionseffekt abbilden, bedingt sein.

Häufig wird aber in der Unternehmenspraxis und Politik Kausalität unterstellt. So wurde beispielsweise anhand eines Mittelwertvergleichs festgestellt, dass Teilnehmer an einer Arbeitsbeschaffungsmaßnahme im Durchschnitt nach kürzerer Zeit eine neue Arbeitsstelle finden als Nicht-Teilnehmer (z.B. Hujer, Maurer, & Wellner 1997). Auf Basis dieses Ergebnisses wurde dann häufig die Schlussfolgerung gezogen, dass Arbeitsbeschaffungsmaßnahmen eine wirkungsvolle Maßnahme zur Senkung der Arbeitslosigkeit seien. Diese Schlussfolgerung kann jedoch so nicht erfolgen, da die Entscheidung über die Teilnahme an einer Arbeitsbeschaffungsmaßnahme nicht zufällig erfolgt, sondern maßgeblich von den Betroffenen mitgestaltet wird (Hujer, Maurer, & Wellner 1997). So belegt beispielsweise die Untersuchung von Hujer, Caliendo, & Radic (2003), dass vor allem motivierte Arbeitssuchende an einer Arbeitsbeschaffungsmaßnahme teilnehmen. Diese (motivierten) Teilnehmer hätten aber auch ohne die Arbeitsbeschaffungsmaßnahme mit einer höheren Wahrscheinlichkeit schneller eine neue Arbeitsstelle gefunden als die (weniger motivierten) Nicht-Teilnehmer an der Arbeitsbeschaffungsmaßnahme. Der ermittelte Unterschied kann folglich nicht ausschließlich auf die Teilnahme an der Arbeitsbeschaffungsmaßnahme zurückgeführt werden, sondern wird auch durch die Motivation der Probanden bedingt. Es liegt dann ein Selbstselektionseffekt der Arbeitssuchenden bei der Einteilung der beiden Gruppen „Teilnehmer“ und „Nicht-Teilnehmer“ an der Arbeitsbeschaffungsmaßnahme vor. So erscheinen vor diesem Hintergrund beispielsweise die Investitionen in Höhe von 138 Milliarden Euro für aktive Arbeitsmarktpolitik in Ostdeutschland in einem anderen Licht (Bundesanstalt für Arbeit 2003).

Auch bei Untersuchungen, die den Einfluss der Vertriebswegenutzung auf die Kundenprofitabilität zu bestimmen versuchen, wurde ein kausaler Zusammenhang unterstellt. Ein Mittelwertvergleich hat hier gezeigt, dass Kunden, die das Internet nutzen, eine höhere Profitabilität aufweisen als Kunden, die das Internet nicht nutzen (Rasch & Lintner 2001; Wehrling 2002). Daraus wurde die Schlussfolgerung gezogen, dass die Internetnutzung einen positiven Einfluss auf die Profitabilität der Kunden hat. Diese Studien vernachlässigen jedoch, dass sich Kunden, die das Internet nutzen, von Kunden, die das Internet nicht nutzen, signifikant unterscheiden. Es liegt demnach ein Selbstselektionseffekt vor (Degeratu, Rangaswamy, & Wu 2000) und es ist nicht möglich, die höhere Profitabilität von Kunden, die das Internet nutzen, gänzlich auf die Internetnutzung zurückzuführen. Dies gilt auch, wenn ein Unternehmen eine Kundenkarte einführt und auf Basis eines Vergleichs der beiden Gruppen „Besitzer der Kundenkarte“ und „Nicht-Besitzer der Kundenkarte“ zu dem Ergebnis kommt, dass die Kunden, die die Kundenkarte besitzen, einen höheren Umsatz tätigen und dass daher die Kundenkarte offensiv vertrieben werden soll. In diesem Beispiel könnte es sein, dass Kunden mit hohem Einkommen in der Regel mehr Umsatz generieren und gleichfalls eine höhere Wahrscheinlichkeit für den Besitz der Kundenkarte haben.

Zur Berücksichtigung des Selbstselektionseffekts ist zum Beispiel in der Medizin (z. B. Singer 1986; D'Agostino 1998) und der Volkswirtschaftslehre (z. B. LaLonde 1986; Heckman et al. 1996; Ashenfelter & Rouse 1998) die so genannte Matching Methode als ein nicht parametrisches Verfahren vorgeschlagen worden. Diese Methode hat jedoch in der Betriebswirtschaftslehre bislang kaum Beachtung gefunden. Ausnahmen stellen beispielsweise Hitt & Frei (2002), Christensen et al. (2004) und Degeratu, Rangaswamy, & Wu (2000) dar. Diese Studien zeigen, dass Selbstselektionseffekte existieren und dass die Berücksichtigung dieser Selbstselektionseffekte für eine adäquate Evaluierung der Effektivität von Maßnahmen entscheidend ist.

Aus diesem Grund ist es das Ziel dieses Beitrags, aufzuzeigen, wie Selbstselektionseffekte berücksichtigt werden können, um eine adäquate Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu gewährleisten. Hierfür wird die Matching Methode dargestellt und es werden verschiedene Varianten der Durchführung der Matching Methode diskutiert. Bei der Darstellung der Matching Methode besteht das Ziel darin, den Einfluss unterschiedlicher Varianten bei der Anwendung der Matching Methode auf die Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable aufzuzeigen. Um dieses Ziel zu erreichen, wird ein illustratives Beispiel aufgegriffen. Letztlich soll dieser Aufsatz verdeutlichen, inwieweit die Matching Methode einen Beitrag leisten kann, bei betriebswirtschaftlichen Fragestellungen eine angemessene Berücksichtigung des Selbstselektionseffekts zu gewährleisten.

Der Beitrag ist daher wie folgt gegliedert. In Abschnitt 2 wird zunächst das Problem der Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable beschrieben. In Abschnitt 3 wird dann die Matching Methode dargestellt und diskutiert. Darauf aufbauend werden dann in Abschnitt 4 Verfahren vorgestellt, die es erlauben, den Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable bei Berücksichtigung des Selbstselektionseffekts zu evaluieren. Diese Ausführungen werden anhand eines illustrativen Beispiels verdeutlicht. Der Beitrag schließt in Abschnitt 5 mit einem Fazit.

2 Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable

Um die vorangegangenen Fragestellungen bezüglich des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu beantworten, ist der folgende Zusammenhang relevant:

(1) $\Delta_i = Y_i^1 - Y_i^0 \qquad \forall i \in I$

mit

Δ_i: Veränderung des Werts der Ergebnisvariablen für den i-ten Teilnehmer der Maßnahme,

Y_i^1: Wert der Ergebnisvariablen für den i-ten Teilnehmer der Maßnahme,

Y_i^0: Wert der Ergebnisvariablen für den i-ten Teilnehmer, wenn er nicht an der Maßnahme teilgenommen hätte,

I: Indexmenge der Teilnehmer an der Maßnahme.

Um den Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu prüfen, wird somit der Wert der Ergebnisvariablen bei Teilnahme an der Maßnahme verglichen mit dem Wert der Ergebnisvariablen, wenn der Teilnehmer nicht an der Maßnahme teilgenommen hätte. Besteht ein signifikanter Unterschied zwischen den beiden Werten der Ergebnisvariablen, so drückt diese Differenz die Größe des Effekts der Teilnahme an der Maßnahme auf die Ergebnisvariable aus. Es wird dann entsprechend des Kausalitätsbegriffs nach Roy (1951) und Rubin (1974) ein kausaler Zusammenhang zwischen der Teilnahme an der Maßnahme und der Ergebnisvariablen postuliert. Dieses Verständnis von Kausalität unterscheidet sich von dem Kausalitätsbegriff nach Granger (1969). Denn Granger (1969) geht von Kausalität aus, wenn eine Variable y bei Berücksichtigung vergangener Werte der Variable x besser prognostiziert werden kann als wenn diese Variable nicht berücksichtigt wird. Beiden Kausalitätsbegriffen ist jedoch gemeinsam, dass diese eine eindeutige Richtung des Zusammenhangs zugrunde legen. So gehen die Kausalitätsbegriffe nach Roy/Rubin und Granger über einen rein assoziativen Zusammenhang hinaus.

Allerdings ist die Differenz der Werte der Ergebnisvariablen nicht beobachtbar (vgl. Tabelle 1). So ist beispielsweise für einen Kunden, der im Besitz einer Kundenkarte ist, der Umsatz bei Besitz der Kundenkarte beobachtbar, aber der Umsatz dieses Kunden ist nicht beobachtbar, wenn er keine Kundenkarte besitzen würde. Dieser fehlende Wert wird auch als „Counterfactual Outcome“ bezeichnet (Hujer, Caliendo, & Radic 2003, S. 11). Daher handelt es sich bei der Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable um ein Problem fehlender Daten. Denn für die Teilnehmer kann nicht beobachtet werden, welchen Wert die Ergebnisvariable aufweisen würde, wenn sie nicht an der Maßnahme teilgenommen hätten und für die Nicht-Teilnehmer kann nicht beobachtet werden, welchen Wert die Ergebnisvariable aufweisen würde, wenn sie an der Maßnahme teilgenommen hätten. Dieses Problem fehlender Daten wird auch als fundamentales Evaluierungsproblem bezeichnet (Imbens 2004, S. 5). Aufgrund dieses fundamentalen Evaluierungsproblems ist es im vorangegangen Beispiel nicht möglich, den individuellen Effekt der Kundenkarte auf den Umsatz eines Kunden direkt zu messen.

Tabelle 1: Beobachtbarkeit der zustandsabhängigen Werte der Ergebnisvariablen

	Zustandsabhängige Werte der Ergebnisvariablen	
	$Y^1_{i(j)}$ Ergebnis bei Teilnahme	$Y^0_{i(j)}$ Ergebnis bei Nicht-Teilnahme
Teilnehmer i	Y^1_i Beobachtbar	Y^0_i Nicht-beobachtbar
Nicht-Teilnehmer j	Y^1_j Nicht-beobachtbar	Y^0_j Beobachtbar

mit

Y^1_j: Wert der Ergebnisvariablen für den j-ten Nicht-Teilnehmer, wenn er an der Maßnahme teilgenommen hätte,

Y^0_j: Wert der Ergebnisvariablen für den j-ten Nicht-Teilnehmer der Maßnahme.

Da das Counterfactual Outcome für die Teilnehmer nicht beobachtbar ist, wird meist der Wert der Ergebnisvariablen für die Nicht-Teilnehmer herangezogen, um den Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable zu evaluieren. Es wird dann ein Mittelwertvergleich für unabhängige Stichproben genutzt (Bortz 1999, S. 137 f.). Im Beispiel würde demnach der Umsatz der Kunden, die eine Kundenkarte besitzen, mit dem Umsatz jener Kunden verglichen, die keine Kundenkarte besitzen. Es erfolgt somit kein individueller Vergleich, sondern ein aggregierter Vergleich der beiden Gruppen:

(2) $$\Delta = E\left[Y^1_i\right] - E\left[Y^0_j\right]$$

mit

Δ: durchschnittliche Veränderung des Werts der Ergebnisvariablen,

$E\left[Y^1_i\right]$: durchschnittlicher Wert der Ergebnisvariablen für die Teilnehmer an der Maßnahme,

$E\left[Y^0_j\right]$: durchschnittlicher Wert der Ergebnisvariablen für die Nicht-Teilnehmer an der Maßnahme.

Der dargestellte Vergleich der Gruppenmittelwerte basiert jedoch auf der Annahme, dass die Zuordnung der Probanden auf die beiden Gruppen zufällig erfolgt und somit Unabhängigkeit der beiden Gruppen vorliegt. In dem angeführten Beispiel der Kundenkarte könnte allerdings das Einkommen der Kunden die Vergabe der Kundenkarte beeinflussen, wenn diese an die Bonität der Kunden gekoppelt ist. Um diese Effekte kontrollieren zu können, ist es notwendig, dass diese Störvariablen berücksichtigt und als Kontrollvariablen erfasst werden.

Basierend darauf, inwieweit diese Störvariablen kontrolliert werden können, wird zwischen einer experimentellen und einer quasi-experimentellen Untersuchung unterschieden. Bei einer experimentellen Untersuchung ist es möglich, die Probanden zufällig den Gruppen zuzuordnen, so dass die Störvariablen unter den Untersuchungsbedingungen annähernd gleich verteilt sind (Randomisierung der Stichprobe) und somit Unabhängigkeit der Gruppen unterstellt werden kann. Dies impliziert, dass die beiden Gruppen sich hinsichtlich der Störvariablen nicht systematisch unterscheiden. Der oben beschriebene Mittelwertvergleich kann dann weiterhin angewendet werden.

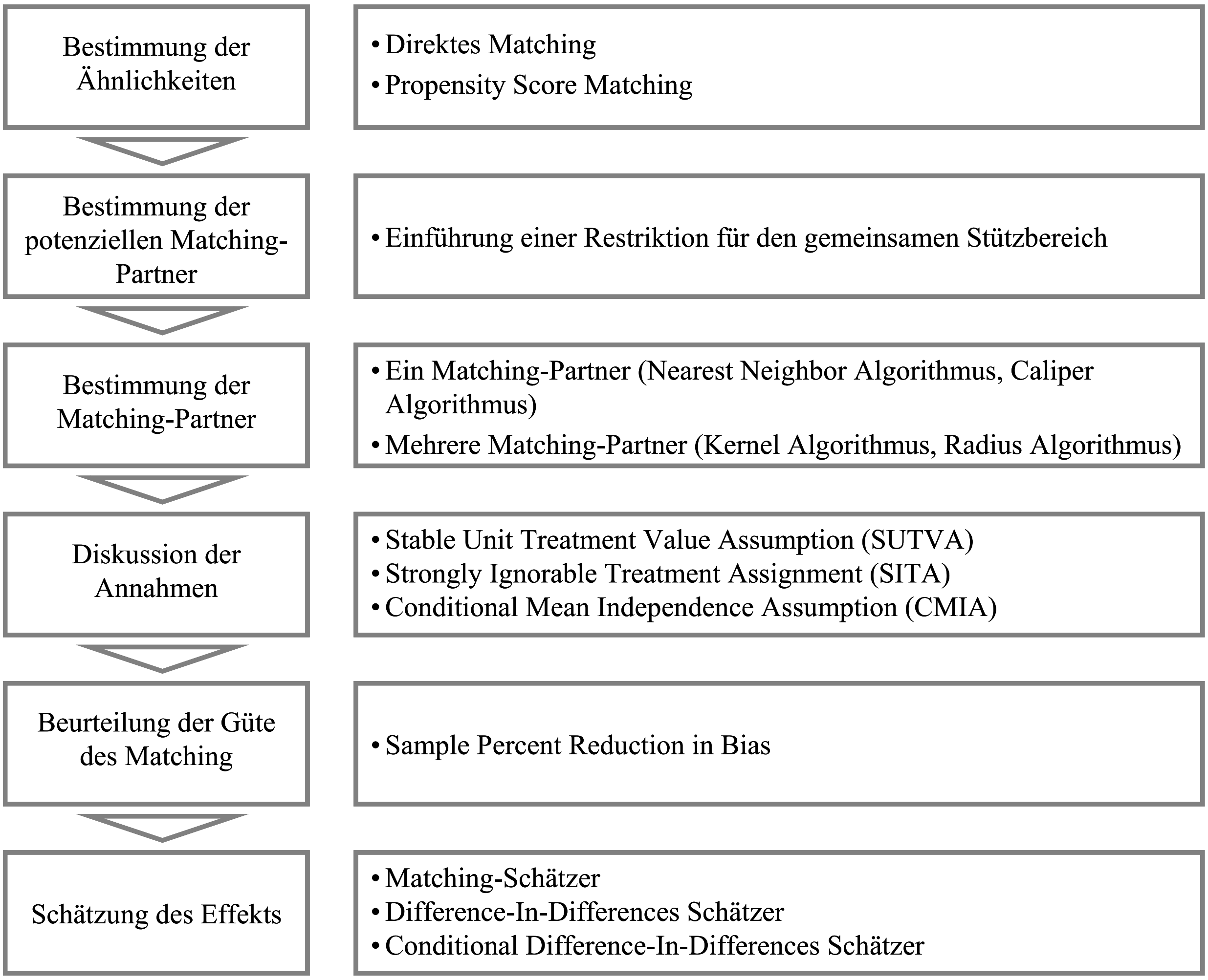
Häufig sind die Gruppen aber bereits gegeben und es ist nicht möglich, die Probanden diesen zufällig zuzuordnen. Da es dann möglich ist, dass das Ergebnis des Mittelwertvergleichs von Störvariablen überlagert wird, gilt es, im Nachhinein ein experimentelles Design nachzubilden, indem eine Berücksichtigung der Störvariablen erfolgt. In diesem Fall liegt eine quasi-experimentelle Untersuchung vor und eine Evaluierung des Effekts der Teilnahme an einer Maßnahme auf die Ergebnisvariable ist dann möglich. In dem angeführten Beispiel würde dies bedeuten, dass das Einkommen eines Kunden sowohl einen Effekt auf den Besitz der Kundenkarte als auch auf den Umsatz eines Kunden hat. Besitzen beispielsweise vor allem Kunden mit hohem Einkommen aufgrund der Vergabekriterien die Kundenkarte, so kann ein beobachteter höherer Umsatz der Kunden mit Kundenkarte im Vergleich zu jenen Kunden ohne Kundenkarte nicht ausschließlich dem Besitz der Kundenkarte zugerechnet werden. Vielmehr liegt dann ein Selbstselektionseffekt vor (Lee 2000, S. 383). Ist nur von Interesse, ob die Kunden, die eine Kundenkarte besitzen einen höheren Umsatz erzielen, so ist es nicht erforderlich dem Selbstselektionseffekt Rechnung zu tragen. Ist aber hingegen der Effekt des Besitzes der Kundenkarte auf den Umsatz eines Kunden von Interesse, so ist die Berücksichtigung der Störvariablen in Form von Kontrollvariablen bei der Evaluierung des Effekts von Bedeutung, um den Selbstselektionseffekt zu berücksichtigen.

So kann die Validität quasi-experimenteller Untersuchungen erhöht werden, indem die zu vergleichenden Gruppen nach allen relevanten Störvariablen parallelisiert werden (matched sample). Im Folgenden wird daher die Matching Methode beschrieben, die eine Parallelisierung der beiden Gruppen erlaubt und somit einem möglichen Selbstselektionseffekt Rechnung trägt.

3 Matching Methode

Die Matching Methode wurde bisher im ökonomischen Bereich vor allem in der volkswirtschaftlichen Literatur angewendet und nimmt eine Parallelisierung von zwei Gruppen vor (z. B. Heckman 1976; Ashenfelter 1978; Heckman 1978; Heckman 1979; Bjorklund & Moffitt 1987; Lechner 2002). Ziel der Matching Methode ist es, systematische Unterschiede in den Störvariablen zwischen der Gruppe der Teilnehmer und der Nicht-Teilnehmer an einer Maßnahme zu eliminieren (Heckman et al. 1996). So kann die nicht-zufällige Zuordnung der Probanden zu den Gruppen beseitigt und das Design einer experimentellen Untersuchung nachgebildet werden. Um dieses Ziel zu erreichen, werden „Zwillingspaare“ aus der Gruppe der Teilnehmer und Nicht-Teilnehmer gebildet, die sich bezüglich der relevanten Störvariablen gleichen und sich nur bezüglich des Teilnahmestatus unterscheiden (Hujer, Caliendo, & Radic 2003, S. 18). Somit werden jedem Teilnehmer ein oder mehrere Nicht-Teilnehmer als Matching-Partner zugeordnet. Auf Basis der ermittelten Matching-Partner kann dann das Counterfactual Outcome bestimmt und so der Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable evaluiert werden. Die Bestimmung der Matching-Partner führt dazu, dass sich die Verteilungen der Störvariablen der Teilnehmer und Nicht-Teilnehmer an der Maßnahme angleichen. Mit anderen Worten, systematische Unterschiede in den Störvariablen der Teilnehmer und Nicht-Teilnehmer werden so eliminiert und damit die bei einem Experiment vorliegenden Bedingungen erreicht. Ein anschließender Mittelwertvergleich erlaubt dann eine unverzerrte Schätzung des Effekts der Teilnahme an der Maßnahme auf die Ergebnisvariable. Im Folgenden wird nun die Vorgehensweise der Matching Methode detailliert beschrieben (siehe Abbildung 1).

Abbildung 1: Vorgehensweise der Matching Methode



3.1 Bestimmung der Ähnlichkeiten der Teilnehmer und Nicht-Teilnehmer

Um die Matching-Partner zu identifizieren, ist es erforderlich, die Ähnlichkeit der Teilnehmer und Nicht-Teilnehmer zu spezifizieren. Dabei kann unterschieden werden, ob ein Matching der Teilnehmer und Nicht-Teilnehmer auf der Basis einzelner Störvariablen erfolgt (direktes Matching) oder ob ein so genannter Propensity Score für das Matching herangezogen wird. In beiden Fällen ist es erforderlich, zunächst jene Variablen zu identifizieren, die die Teilnahme an der Maßnahme und die Ergebnisvariable beeinflussen und daher den Selbstselektionseffekt determinieren. Bei einem direkten Matching werden dann diese Störvariablen herangezogen, um die Matching-Partner zu finden. Hierbei gilt es für jeden Teilnehmer einen Nicht-Teilnehmer zu identifizieren, dessen Ausprägungen der Störvariablen mit jenen des Teilnehmers übereinstimmen. Dieses Vorgehen eignet sich für Anwendungen, bei denen nur wenige Störvariablen zu berücksichtigen sind. Bei einer Vielzahl von Störvariablen erweist sich das direkte Matching jedoch als nicht praktikabel, denn die Anwendung führt zu einem Dimensionalitätsproblem (Hujer, Caliendo, & Radic 2001, S. 178). Dieses Dimensionalitätsproblem besteht darin, dass es sich sehr schwierig gestaltet einen Matching-Partner zu identifizieren, der in allen Störvariablen dem Teilnehmer an der Maßnahme gleicht. Eine Berücksichtigung aller Störvariablen ist jedoch erforderlich, um den Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable adäquat evaluieren zu können. Es kommt dann zu dem folgenden Trade-Off: Je mehr beobachtete Störvariablen berücksichtigt werden, desto besser ist die Evaluierung des Selbstselektionseffekts, desto wahrscheinlicher ist es aber auch, dass für einen Teilnehmer kein geeigneter Matching-Partner gefunden wird.

Rosenbaum & Rubin (1983) schlagen daher zur Lösung des Dimensionalitätsproblems das Propensity Score Matching vor. Dabei werden die Matching-Partner in der Art bestimmt, dass sich deren Propensity Scores P(X) annähernd entsprechen. Der Propensity Score P(X) ist eine Funktion der Störvariablen X und ist definiert als die Wahrscheinlichkeit der Teilnahme an der Maßnahme. Bei der Bildung von Matching-Partnern werden also alle relevanten und beobachteten Störvariablen X indirekt durch deren Einfluss auf den Propensity Score P(X) berücksichtigt. Daher reduziert sich das Problem des Auffindens eines Matching-Partners auf eine Dimension und zwar auf den Wert des Propensity Scores P(X) (D'Agostino 1998, S. 2267). Der Propensity Score wird üblicherweise mittels Probit- oder Logit-Modellen (siehe Gleichung (3)) geschätzt, bei denen die abhängige Variable die getroffene Teilnahmeentscheidung darstellt (Dehejia & Wahba 2002).

(3) $$P_h(X) = \frac{1}{1+\exp(\beta' \cdot X_h)} \qquad \forall\, h \in H$$

mit

$P_h(X)$: Wahrscheinlichkeit, dass der h-te Proband an der Maßnahme teilnimmt,

β: Vektor der Parameter für die Störvariablen,

X_h: Vektor der Ausprägungen der Störvariablen für den h-ten Probanden,

H: Indexmenge der Probanden (entspricht der Menge aller Teilnehmer und Nicht-Teilnehmer: $H = I \cup J$).

Da die Bildung des Propensity Scores die Grundlage für das Auffinden der Matching-Partner ist, ist es empfehlenswert, die Spezifikation des Modells zu testen (Lechner 1998; Cox

& Wermuth 2004). So ist es zum Beispiel sinnvoll, die Signifikanz der berücksichtigten Störvariablen zu überprüfen.

In Anlehnung an das Beispiel der Kundenkarte würde die Variable „Besitz der Kundenkarte“ als abhängige Variable für den Propensity Score verwendet werden. Die unabhängigen Variablen werden durch die beobachteten Störvariablen repräsentiert. Hierfür könnten beispielsweise das Einkommen der Kunden oder weitere Variablen wie das Geschlecht oder die Wohnregion in Betracht kommen. Es kann nun das Modell geschätzt werden, das jedem Teilnehmer und Nicht-Teilnehmer einen Propensity Score zuordnet und damit eine Wahrscheinlichkeit für den Besitz der Kundenkarte. Statt nun die einzelnen Störvariablen heranzuziehen, um die Matching-Partner zu identifizieren, wird lediglich der Propensity Score betrachtet. So wird durch die Bildung des Propensity Scores das mehrdimensionale Problem des direkten Matching auf eine Dimension reduziert, was häufig auch in einer Erhöhung der Anzahl der einem Teilnehmer ähnlichen Nicht-Teilnehmer resultiert. Dieser Effekt tritt ein, da nun mit dem Propensity Score eine einzige Variable und nicht mehrere Störvariablen zur Bestimmung der Ähnlichkeit der Teilnehmer und Nicht-Teilnehmer herangezogen wird.

Aufgrund der kompensatorischen Beziehungen zwischen den unabhängigen Variablen im Logit- oder Probit-Modell ist es jedoch möglich, dass Matching-Partner in ihren Propensity Scores übereinstimmen, jedoch nicht in den Ausprägungen ihrer Störvariablen. Aus diesem Grund wird in der neueren Literatur häufig ein hybrider Ansatz angewendet, bei dem neben dem Propensity Score auch einzelne Störvariablen zum Matching herangezogen werden (Lechner 1998). Dies soll dafür Sorge tragen, dass sich die Matching-Partner nicht nur im Propensity Score, sondern auch in einzelnen Störvariablen ähnlich sind.

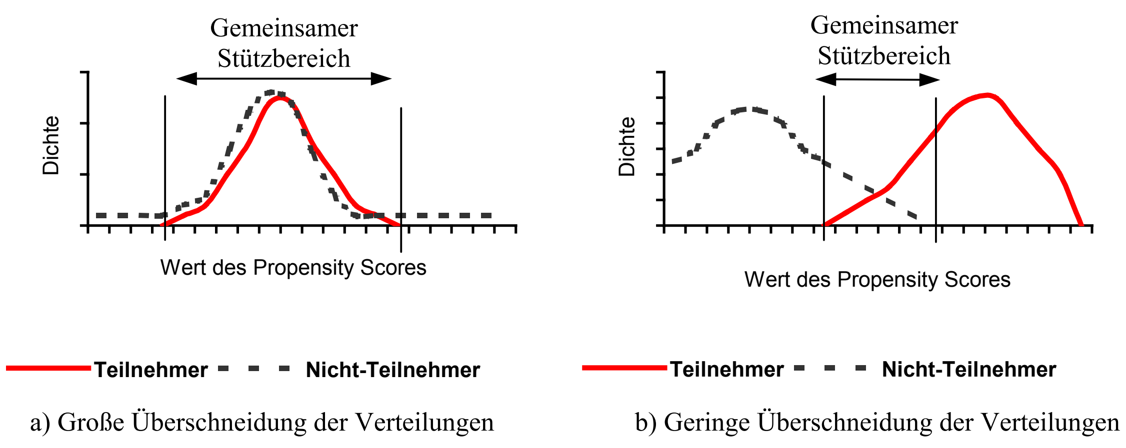
Da es sich bei dem Propensity Score um eine Wahrscheinlichkeit handelt, liegen im Intervall [0,1] unendlich viele Ausprägungen des Propensity Scores vor. Aus diesem Grund ist es üblicherweise bei einem Matching auf Basis des Propensity Scores nicht möglich, eine exakte Übereinstimmung zwischen dem Propensity Score eines Teilnehmers und eines Nicht-Teilnehmers zu erreichen. Mehrere Algorithmen stehen nun zur Verfügung, um Matching-Partner zu identifizieren, die keine exakte Übereinstimmung zwischen den Propensity Scores voraussetzen. Hierbei gilt es die Menge der Nicht-Teilnehmer zu identifizieren, die der Menge der Teilnehmer möglichst ähnlich ist. Die Ähnlichkeit wird durch eine geringe Differenz zwischen den Propensity Scores der Teilnehmer und Nicht-Teilnehmer ausgedrückt. Im Folgenden wird daher zunächst beschrieben, wie die Menge an potenziellen Matching-Partnern für die Teilnehmer an der Maßnahme bestimmt werden kann und dann werden die am häufigsten eingesetzten Algorithmen zur Bestimmung der Matching-Partner vorgestellt.

3.2 Bestimmung der potenziellen Matching-Partner

Die Propensity Scores der Teilnehmer und Nicht-Teilnehmer bilden zwei Verteilungen. Um geeignete Matching-Partner zu identifizieren, ist es erforderlich, dass sich die Wertebereiche der Verteilungen der Propensity Scores der Teilnehmer und Nicht-Teilnehmer überschneiden. Denn nur dann ist sichergestellt, dass hinreichend ähnliche Matching-Partner identifiziert werden können. Dieser Überschneidungsbereich der beiden Verteilungen wird als gemeinsamer Stützbereich (Region of Common Support) bezeichnet (Heckman, Ichimura, & Todd 1998).

Um sicher zu stellen, dass sich die Matching-Partner möglichst ähnlich sind, kann eine Restriktion für den gemeinsamen Stützbereich eingeführt werden. In diesem Fall werden die Nicht-Teilnehmer und Teilnehmer eliminiert und damit nicht zum Matching herangezogen, deren Propensity Scores außerhalb des gemeinsamen Stützbereichs liegen. Dieser Zusammenhang wird in Abbildung 2 verdeutlicht. So kann die Einführung einer Restriktion für den gemeinsamen Stützbereich helfen, ähnliche Matching-Partner zu identifizieren. Es muss jedoch beachtet werden, dass die Einführung einer Restriktion für den gemeinsamen Stützbereich dazu führen kann, dass lediglich der Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable für einen Teil der Stichprobe bestimmt wird.

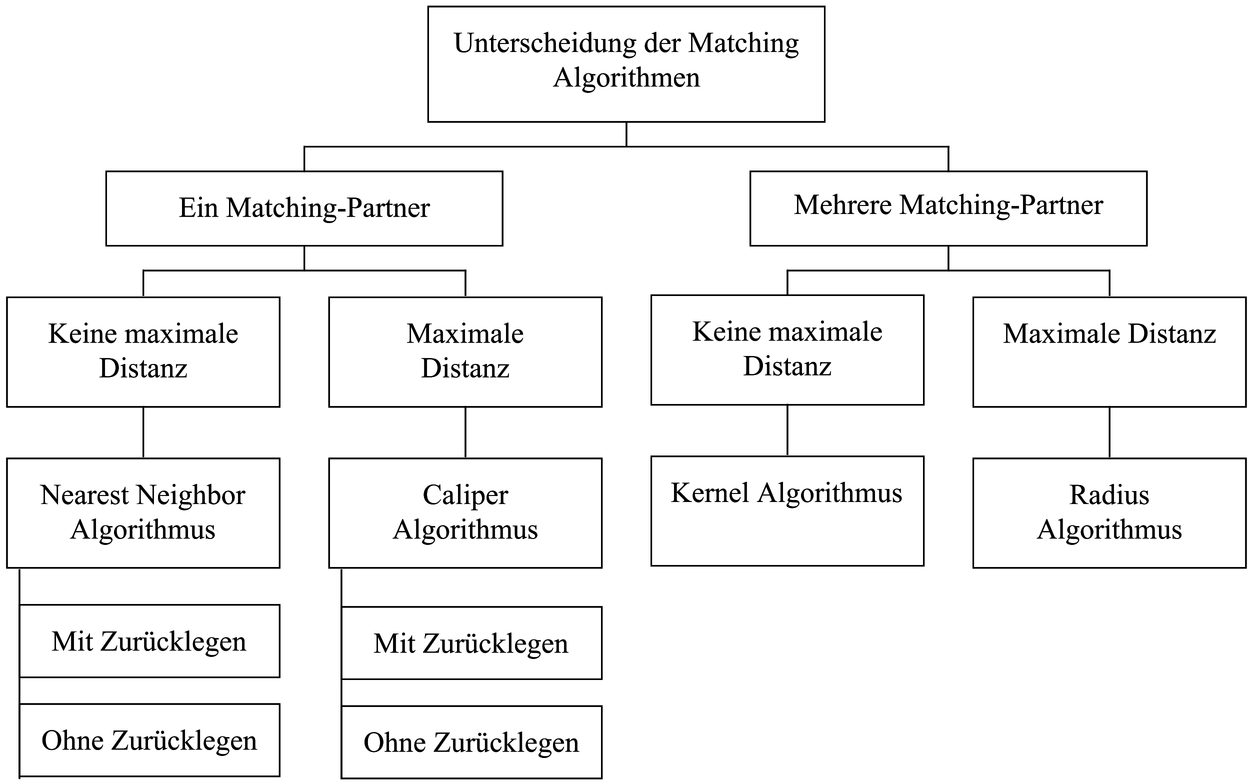
Abbildung 2: Darstellung des gemeinsamen Stützbereichs



3.3 Bestimmung der Matching-Partner

Bei der Bestimmung der Matching-Partner kann grundsätzlich unterschieden werden, ob nur ein Nicht-Teilnehmer oder ob mehrere Nicht-Teilnehmer als Matching-Partner herangezogen werden. Zudem kann differenziert werden, ob eine maximale Distanz zwischen den Matching-Partnern berücksichtigt wird und ob ein Matching mit oder ohne Zurücklegen der Nicht-Teilnehmer erfolgt. So können die Alternativen zur Bestimmung der Matching-Partner, wie in Abbildung 3 dargestellt, unterteilt werden.

Abbildung 3: Algorithmen zur Bestimmung der Matching-Partner



Berücksichtigung eines Matching-Partners

Bei der Berücksichtigung genau eines Nicht-Teilnehmers als Matching-Partner für einen Teilnehmer an der Maßnahme kann zwischen dem Nearest Neighbor Algorithmus und dem Caliper Algorithmus unterschieden werden.

Beim Nearest Neighbor Algorithmus wird jedem Teilnehmer i jener Nicht-Teilnehmer j als Matching-Partner zugeordnet, der die geringste Distanz zu dem Teilnehmer aufweist. So wird die Nachbarschaft eines Teilnehmers C_i durch den Nicht-Teilnehmer definiert, dessen Distanz zum Propensity Score des Teilnehmers am geringsten ist:

$$(4) \qquad C_i = \left\{ j \,\middle|\, \left\| P_i(X) - P_j(X) \right\| = \min_{j' \in J} \left\| P_i(X) - P_{j'}(X) \right\| \right\} \quad \forall\, i \in I$$

Diesem Matching-Partner j wird das Gewicht w(i,j)=1 zugewiesen. Demnach ist w(i,j) gegeben durch (Heckman et al. 1998, S. 1024):

$$(5) \qquad w_{i,j}^{NN} = \begin{cases} 1, & \text{falls } j \in C_i \\ 0 & \text{sonst.} \end{cases} \quad \forall\, i \in I, j \in J$$

Es ist möglich, dass mehr als ein Nicht-Teilnehmer in der Menge C_i enthalten ist. Dieser Fall wird jedoch in der Literatur bislang nicht thematisiert. In diesem besonderen Fall wird daher die Auswahl des Matching-Partners durch die spezifische Umsetzung des Algorithmus in der verwendeten Software getroffen. Die Auswahl des Matching-Partners kann zum Beispiel nach der Reihenfolge der gefundenen Nachbarn erfolgen. So wird dann bei mehreren gleich weit entfernten Nachbarn beispielsweise der zuerst identifizierte Nachbar herangezogen.

Im Gegensatz zum Nearest Neighbor Algorithmus wird beim Caliper Algorithmus eine maximale Distanz der Matching-Partner berücksichtigt (Dehejia & Wahba 2002, S. 153). Es wird ein Toleranz-Wert ε eingeführt:

$$(6) \qquad C_i = \left\{ j \,\middle|\, \left\| P_i(X) - P_j(X) \right\| = \min_{j' \in J} \left\| P_i(X) - P_{j'}(X) \right\| \wedge \left\| P_i(X) - P_j(X) \right\| < \varepsilon \right\} \quad \forall\, i \in I$$

Diesen Toleranz-Wert darf die Differenz der Propensity Scores $P_i(X)$ und $P_j(X)$ nicht überschreiten. Ist dieses Kriterium für keinen Nicht-Teilnehmer erfüllt, weist also die in (6) dargestellte Menge keine Elemente auf, dann wird der Teilnehmer i ausgeschlossen. Weist die Menge C_i allerdings einen Nicht-Teilnehmer als Element auf, dann wird diesem ein Gewicht von eins zugewiesen, wohingegen allen anderen Nicht-Teilnehmern ein Gewicht von Null zugewiesen wird (Heckman et al. 1998, S. 1024). So gilt:

$$(7) \qquad w_{i,j}^{CM} = \begin{cases} 1, & \text{falls } j \in C_i \\ 0 & \text{sonst.} \end{cases} \quad \forall\, i \in I, j \in J$$

So entspricht das Ergebnis des Caliper Algorithmus dann dem des Nearest Neigbor Algorithmus, wenn der Toleranzwert in der Art und Weise festgelegt wird, dass immer ein Nicht-Teilnehmer als Matching-Partner identifiziert wird.

Zudem besteht ein Zusammenhang zwischen der Berücksichtigung einer Restriktion für den gemeinsamen Stützbereich und der Höhe des Toleranzwerts. Bei einem geringen Wert für den Toleranzwert und keiner Berücksichtigung einer Restriktion für den gemeinsamen Stützbereich ist gewährleistet, dass die Matching-Partner sich relativ ähnlich sind, auch wenn diese außerhalb der Restriktion für den gemeinsamen Stützbereich liegen. Dennoch ist bei einem sehr geringen Wert für den Toleranzwert auch bei einem großen gemeinsamen Stützbereich nicht garantiert, dass ein Matching-Partner identifiziert werden kann.

Bei einem Matching ohne Zurücklegen wird jeder Nicht-Teilnehmer maximal einmal als Matching-Partner herangezogen. Weisen die Teilnehmer überwiegend hohe Werte, die Nicht-Teilnehmer hingegen überwiegend geringe Werte für den Propensity Score auf, dann werden zunächst die wenigen Nicht-Teilnehmer mit hohen Werten für den Propensity Score als Matching-Partner herangezogen. Im weiteren Verlauf stehen in der Gruppe der Nicht-Teilnehmer jedoch nur noch Teilnehmer mit einem geringen Wert für den Propensity Score zur Verfügung. Dies führt dazu, dass für die Teilnehmer zunehmend unähnlichere Nicht-Teilnehmer als Matching-Partner ausgewählt werden oder bei Anwendung des Caliper Algorithmus kein Nicht-Teilnehmer mehr als Matching-Partner identifiziert werden kann. Auch wird durch die Reihenfolge der Zuordnung der Matching-Partner die Auswahl der Matching-Partner beeinflusst. Um dem Problem des Auffindens immer unähnlicherer Matching-Partner zu begegnen, kann ein Matching mit Zurücklegen durchgeführt werden.

Bei einem Matching mit Zurücklegen kann ein Nicht-Teilnehmer mehrfach als Matching-Partner für verschiedene Teilnehmer herangezogen werden. Weisen zum Beispiel zwei Teilnehmer der Maßnahme den gleichen Propensity Score auf, können sie auch dem gleichen Nicht-Teilnehmer zugeordnet werden. Aus diesem Grund ist das Matching mit Zurücklegen generell mit einer größeren Ähnlichkeit der Matching-Partner verbunden (Smith & Todd 2000, S. 1). Andererseits birgt das Matching mit Zurücklegen, insbesondere bei extrem unterschiedlichen Verteilungen der Propensity Scores der Teilnehmer und Nicht-Teilnehmer, das Problem, dass wenige Nicht-Teilnehmer sehr häufig als Matching-Partner verwendet werden. Dies führt dazu, dass die Evaluierung des Effekts der Teilnahme an der Maßnahme auf die Ergebnisvariable auf Basis einer sehr kleinen Stichprobe von Nicht-Teilnehmern erfolgt. Dadurch sinkt jedoch die Stabilität der Schätzung des Effekts der Teilnahme an der Maßnahme auf die Ergebnisvariable. Wird zum Beispiel ein Nicht-Teilnehmer aus der Datenbasis entfernt, kann dies zu starken Änderungen des Werts des ermittelten Effekts der Teilnahme an der Maßnahme auf die Ergebnisvariable führen.

Berücksichtigung mehrerer Matching-Partner

Bei der Berücksichtigung mehrerer Nicht-Teilnehmer als Matching-Partner für einen Teilnehmer an der Maßnahme wird zwischen dem Kernel Algorithmus und dem Radius Algorithmus unterschieden.

Der Kernel Algorithmus geht von der Annahme aus, dass jeder Nicht-Teilnehmer zumindest in gewissem Umfang als Matching-Partner geeignet ist. So werden für jeden Teilnehmer alle Nicht-Teilnehmer als Matching-Partner herangezogen (Hujer, Caliendo, & Radic 2001, S. 180).

$$(8) \qquad C_i = \{J\} \qquad \forall\ i \in I$$

Dabei erhalten Nicht-Teilnehmer, die eine geringe Distanz zu einem Teilnehmer aufweisen, ein hohes Gewicht und Nicht-Teilnehmer mit einer großen Distanz bekommen ein geringes Gewicht zugewiesen (Hujer, Caliendo, & Radic 2003, S. 68).

$$(9) \qquad w_{i,j}^{KM} = \frac{K\left(\frac{P_i(X) - P_j(X)}{\tau}\right)}{\sum_{j' \in C_i} K\left(\frac{P_i(X) - P_{j'}(X)}{\tau}\right)} \qquad \forall\ i \in I, j \in J$$

mit

τ: Bandbreitenparameter,

$K(\cdot)$: Kernel-Funktion (z.B. Gauß'sche Normalverteilung).

Der Bandbreitenparameter ist durch den Anwender festzulegen (Smith & Todd 2000). Dieser beeinflusst das Gewicht, das ein Nicht-Teilnehmer als Matching-Partner für einen Teilnehmer an der Maßnahme erhält. So führt eine Senkung des Bandbreitenparameters bei einer Normalverteilung als Kernel-Funktion dazu, dass Nicht-Teilnehmer mit einer größeren Distanz zu dem Teilnehmer ein geringeres Gewicht erhalten. Dennoch berücksichtigt der Kernel Algorithmus keine maximale Distanz zwischen den Matching-Partnern, sondern zieht alle Nicht-Teilnehmer heran. Dagegen wird beim Radius Algorithmus eine maximale Distanz der Matching-Partner berücksichtigt. So ergibt sich die Nachbarschaft eines Teilnehmers bei dem Radius Algorithmus aus:

$$(10) \qquad C_i = \left\{ j \middle| \; \left\| P_i(X) - P_j(X) \right\| < \varepsilon \right\} \qquad \forall\, i \in I$$

Es werden dann alle Nicht-Teilnehmer gleich gewichtet als Matching-Partner herangezogen, deren Distanz zu einem Teilnehmer den Toleranzwert nicht überschreitet:

$$(11) \qquad w_{i,j}^{RM} = \begin{cases} \dfrac{1}{|C_i|}, & \text{falls } j \in C_i \\ 0 & \text{sonst.} \end{cases} \qquad \forall\, i \in I, j \in J$$

mit

$|C_i|$: Anzahl der Elemente in der Menge C_i.

Eine abschließende Beurteilung der unterschiedlichen Algorithmen ist nicht möglich, da es von der zu untersuchenden Fragestellung abhängt, welcher der vorgestellten Algorithmen sich als vorteilhaft erweist. Häufig angewendet werden der Nearest Neighbor Algorithmus und der Kernel Algorithmus (z. B. Lechner 2002; Black & Smith 2004), da die Bestimmung des Toleranzwerts durch den Anwender beim Caliper und Radius Algorithmus kritisch ist.

3.4 Annahmen der Matching Methode

Der Matching Methode liegen die folgenden Annahmen zugrunde:

- Stable Unit Treatment Value Assumption (SUTVA)
- Strongly Ignorable Treatment Assumption (SITA)
- Conditional Mean Independence Assumption (CMIA)

Die als Stable Unit Treatment Value Assumption (SUTVA) bezeichnete Annahme unterstellt, dass die Teilnahme eines Probanden an der Maßnahme ausschließlich das Verhalten dieses Probanden beeinflusst und keinen Einfluss auf das Verhalten und die Ergebnisvariable anderer Probanden hat (Rubin 1990). So wird im Beispiel unterstellt, dass ein Kunde, der eine Kundenkarte besitzt, nicht das Teilnahmeverhalten und den Umsatz eines anderen Kunden beeinflusst. Diese Annahme ist dann kritisch, wenn beispielsweise Weiterempfehlungen oder auch Netzeffekte von Bedeutung sind. Empfiehlt ein Besitzer der Kundenkarte diese weiter und erwerben dann weitere Kunden die Kundenkarte, so kann nicht mehr davon ausgegangen werden, dass die Stable Unit Treatment Assumption erfüllt ist. Der Vergleich eines Teilnehmers mit einem gematchten Nicht-Teilnehmer würde dann vernachlässigen, dass sich die Teilnahme auch in einem anderen Verhalten von weiteren Teilnehmern niederschlägt.

Die „Strongly Ignorable Treatment Assignment“ (SITA) Annahme besagt, dass nach dem Matching auf die beobachteten Kontrollvariablen die Werte der Ergebnisvariablen nicht durch die Kontrollvariablen beeinflusst werden:

(12) $$(Y_h^1, Y_h^0) \perp D_h \,|\, P(X) \quad \forall\, h \in H$$

mit

D_h: Teilnahmestatus an einer Maßnahme des h-ten Probanden,

Y_h^1: Wert der Ergebnisvariablen für den h-ten Probanden, wenn er an der Maßnahme teilnimmt,

Y_h^0: Wert der Ergebnisvariablen für den h-ten Probanden, wenn er an der Maßnahme nicht teilnimmt.

Wenn die SITA Annahme erfüllt ist, kann der Wert der Ergebnisvariablen für die Nicht-Teilnehmer als Counterfactual Outcome für den Wert der Ergebnisvariablen der Gruppe der Teilnehmer verwendet werden. Ist die SITA Annahme hingegen nicht erfüllt, so kann der Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable nicht angemessen evaluiert werden, da eine Konfundierung vorliegt.

Diese Annahme ist jedoch eine sehr strenge Annahme und Heckman, LaLonde, & Smith (1999) zeigen, dass die so genannte Conditional Mean Independence Assumption (CMIA) ausreicht, um den Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable adäquat evaluieren zu können. Diese Annahme unterstellt lediglich:

(13) $$E\left(Y^1 | D, P(X)\right) = E\left(Y^1 | P(X)\right) \text{ bzw. } E\left(Y^0 | D, P(X)\right) = E\left(Y^1 | P(X)\right)$$

Es werden folglich nur noch die Erwartungswerte der Ergebnisvariablen betrachtet. Ist diese Annahme nicht erfüllt, dann erfolgt lediglich eine verzerrte Schätzung des Effekts der Teilnahme an einer Maßnahme auf die Ergebnisvariable.

Wie im Beispiel der Kundenkarte bereits beschrieben, könnten sich die Besitzer der Kundenkarte systematisch von den Kunden ohne Kundenkarte hinsichtlich ihres Einkommens unterscheiden. Diese Störvariable hat jedoch nicht nur einen Effekt auf die Teilnahmeentscheidung, sondern auch auf die Ergebnisvariable Umsatz. Aus diesem Grund kann nicht eindeutig bestimmt werden, ob eine Änderung der Ergebnisvariablen der Teilnahme an der Maßnahme oder der Störvariablen Einkommen zugeschrieben werden muss. Durch eine Berücksichtigung des Einkommens als Störvariable bei dem Matching wird der Effekt dieser Störvariablen auf die Gruppenzugehörigkeit eliminiert. Somit besitzt das Einkommen keinen weiteren Einfluss auf den Besitz einer Kundenkarte und der Wert der Ergebnisvariablen ist nun unabhängig von dem Besitz einer Kundenkarte.

3.5 Beurteilung der Güte des Matching

Die Güte des Matching hängt davon ab, inwieweit eine Angleichung der Verteilungen der Störvariablen in den beiden Gruppen der Teilnehmer und Nicht-Teilnehmer erreicht werden kann. Das Sample Percent Reduction in Bias ist eine Messgröße, mit der geprüft werden kann, wie stark sich die Störvariablen von Teilnehmern und Nicht-Teilnehmern nach dem Matching angeglichen haben (Rosenbaum & Rubin 1985). Dazu wird für jede einzelne Störvariable der Mittelwert zwischen Teilnehmern und Nicht-Teilnehmern vor und nach Matching verglichen.

(14) $$SB_n = 1 - \frac{\left|\overline{x}_{i,n}^{N} - \overline{x}_{j,n}^{N}\right|}{\left|\overline{x}_{i,n}^{V} - \overline{x}_{j,n}^{V}\right|} \qquad \forall\, n \in N$$

mit

SB_n: Percent Reduction in Bias für die n-te Störvariable,

$\overline{x}_{i,n}^{N}$: Mittelwert der n-ten Störvariablen für die Teilnehmer an der Maßnahme nach Matching,

$\overline{x}_{j,n}^{N}$: Mittelwert der n-ten Störvariablen für die Nicht-Teilnehmer an der Maßnahme nach Matching,

$\overline{x}_{i,n}^{V}$: Mittelwert der n-ten Störvariablen für die Teilnehmer an der Maßnahme vor Matching,

$\overline{x}_{j,n}^{V}$: Mittelwert der n-ten Störvariablen für die Nicht-Teilnehmer an der Maßnahme vor Matching,

N: Indexmenge aller Störvariablen.

Das Sample Percent Reduction in Bias liegt in der Regel im Intervall von 0% bis 100%, da durch das Matching die Differenz der Mittelwerte kleiner wird und somit die Ähnlichkeit der Teilnehmer und Nicht-Teilnehmer bezüglich einer Störvariablen erhöht wird.

4 Schätzung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable

Im Folgenden wird nun beschrieben, wie nach dem Auffinden der Matching-Partner der Effekt der Teilnahme an der Maßnahme auf den Wert der Ergebnisvariablen geschätzt werden kann. Hierfür werden die folgenden Schätzer herangezogen: der Matching-Schätzer, der Difference-In-Differences Schätzer und der Conditional Difference-In-Differences Schätzer. Diese Schätzer haben das Ziel, den durchschnittlichen Effekt der Teilnahme an der Maßnahme auf die Ergebnisvariable – den so genannten durchschnittlichen Treatment-on-Treated Effekt (Average Treatment-on-Treated Effect, kurz: ATTE) – zu schätzen:

(15) $$\Delta^{ATTE} = E\left[Y_i^1\right] - E\left[Y_i^0\right]$$

mit

Δ^{ATTE}: durchschnittlicher Treatment-on-Treated Effekt.

Der Effekt der Teilnahme bei den Nicht-Teilnehmern an der Maßnahme auf die Ergebnisvariable kann analog basierend auf $E\left[Y_j^1\right] - E\left[Y_j^0\right]$ ermittelt werden. Jedoch wird in den empirischen Untersuchungen meist auf den durchschnittlichen Treatment-on-Treated Effekt fokussiert. Aus diesem Grund wird im Folgenden nur dieser Effekt – wie in Gleichung (15) dargestellt – betrachtet.

4.1 Matching-Schätzer

Der Matching-Schätzer basiert auf einem Vergleich der durch das Matching identifizierten Partner von Teilnehmern und Nicht-Teilnehmern an der Maßnahme. Dabei setzt die Anwendung des Matching-Schätzers voraus, dass die bereits in Abschnitt 3.4 beschriebene Conditional Mean Independence Assumption (CMIA) erfüllt ist (Rässler 2002, S. 3). Es gilt dann:

(16) $$E\left[Y_i^0 \middle| P(X)\right] = E\left[Y_j^0 \middle| P(X)\right]$$

mit

$E\left[Y_i^0 \middle| P(X)\right]$: durchschnittlicher Wert der Ergebnisvariablen für die Teilnehmer nach Matching, wenn diese nicht an der Maßnahme teilgenommen hätten (Counterfactual Outcome),

$E\left[Y_j^0 \middle| P(X)\right]$: durchschnittlicher Wert der Ergebnisvariablen für die Nicht-Teilnehmer nach Matching.

Der in Gleichung (16) dargestellte Zusammenhang drückt aus, dass das Counterfactual Outcome für die Teilnehmer an der Maßnahme durch den beobachteten Wert für die Nicht-Teilnehmer ausgedrückt werden kann. Dieser Zusammenhang basiert auf der Annahme, dass der erwartete Wert der Ergebnisvariablen nach dem Matching unabhängig von der Teilnahme an der Maßnahme ist.

So kann der geschätzte durchschnittliche Treatment-on-Treated Effekt in der folgenden Weise ermittelt werden:

$$\begin{aligned} \Delta^{MATTE} &= E\left[Y_i^1 \middle| P(X)\right] - E\left[Y_i^0 \middle| P(X)\right] \\ &= E\left[Y_i^1 \middle| P(X)\right] - E\left[Y_j^0 \middle| P(X)\right] \end{aligned} \tag{17}$$

mit

Δ^{MATTE} : durchschnittlicher Treatment-on-Treated Effekt nach Matching.

Der durchschnittliche Treatment-on-Treated Effekt entspricht somit der Differenz der Mittelwerte der Ergebnisvariablen der Teilnehmer und der gematchten Nicht-Teilnehmer der Maßnahme nach Anwendung der Matching Methode.

Der durchschnittliche Wert der Ergebnisvariablen für die Nicht-Teilnehmer an der Maßnahme ergibt sich dabei in der folgenden Weise:

$$E\left[Y_j^0 \middle| P(X)\right] = \frac{1}{|I|} \sum_{i \in I} \sum_{j \in J} w_{i,j} \cdot Y_j^0 \tag{18}$$

So ergibt sich der durchschnittliche Wert der Ergebnisvariablen für das Counterfactual Outcome der Teilnehmer als gewichteter Mittelwert der Werte der Ergebnisvariablen für die jeweiligen Matching-Partner. Hierbei wird die Gewichtung der Nicht-Teilnehmer durch den angewendeten Algorithmus determiniert.

4.2 Difference-In-Differences Schätzer

Der Difference-In-Differences (DID) Schätzer setzt nicht die Bestimmung von Matching-Partnern voraus, sondern vergleicht die durchschnittliche Veränderung des Wertes der Ergebnisvariablen bei den Teilnehmern vor und nach der Teilnahme an der Maßnahme mit der durchschnittlichen Veränderung der Ergebnisvariablen bei allen Nicht-Teilnehmern (Hujer, Caliendo, & Radic 2003, S. 22).

(19) $\Delta^{DID} = E\left[Y_{i,t}^{1} - Y_{i,t'}^{0}\right] - E\left[Y_{j,t}^{0} - Y_{j,t'}^{0}\right] \qquad t' < t_T < t$

mit

Δ^{DID}: durchschnittlicher Treatment-on-Treated Effekt auf der Basis des Difference-In-Differences Schätzers,

$Y_{i,t(t')}^{1}$: Wert der Ergebnisvariablen für den i-ten Teilnehmer an der Maßnahme zum t(t')-ten Zeitpunkt,

$Y_{j,t(t')}^{0}$: Wert der Ergebnisvariablen für den j-ten Nicht-Teilnehmer an der Maßnahme zum t(t')-ten Zeitpunkt,

t_T: Zeitpunkt der Teilnahme an der Maßnahme.

Aufgrund der beschriebenen Vorgehensweise berücksichtigt der Difference-In-Differences Schätzer einen möglichen Trendeffekt. Hierbei wird angenommen, dass dieser für die Teilnehmer und Nicht-Teilnehmer an der Maßnahme in gleichem Maße vorliegt. Die Vorgehensweise des Difference-In-Differences Schätzers impliziert jedoch auch, dass die durchschnittliche Verzerrung durch den Selbstselektionseffekt in den betrachteten Perioden das gleiche Ausmaß besitzt, so dass diese durch die doppelte Differenzbildung eliminiert werden kann (Heckman et al. 1998, S. 1029). Es liegt dem Difference-In-Differences Schätzer folglich die Annahme zugrunde, dass die Höhe des Selbstselektionseffekts über die Zeit hinweg konstant ist und linear additiv eingeht.

4.3 Conditional Difference-In-Differences Schätzer

Der Conditional Difference-In-Differences (CDID) Schätzer ist eine Kombination des Matching-Schätzers und des Difference-In-Differences Schätzers. So wird der durchschnittliche Treatment-on-Treated Effekt ermittelt, indem die doppelten Differenzen nun in Bezug auf die Matching-Partner gebildet werden. Es wird dabei entsprechend zu Gleichung (16) die folgende Annahme zugrunde gelegt:

(20) $E\left[Y_{i,t}^{0} - Y_{i,t'}^{0} \middle| P(X)\right] = E\left[Y_{j,t}^{0} - Y_{j,t'}^{0} \middle| P(X)\right] \qquad t' < t_T < t$

Der durchschnittliche Treatment-on-Treated Effekt wird dann in der folgenden Weise ermittelt (Heckman, Ichimura, & Todd 1998):

$$\text{(21)} \qquad \begin{aligned} \Delta^{CDID} &= E\left[Y^1_{i,t} - Y^0_{i,t'} \middle| P(X)\right] - E\left[Y^0_{i,t} - Y^0_{i,t'} \middle| P(X)\right] \\ &= E\left[Y^1_{i,t} - Y^0_{i,t'} \middle| P(X)\right] - E\left[Y^0_{j,t} - Y^0_{j,t'} \middle| P(X)\right] \end{aligned} \qquad t' < t_T < t$$

mit

Δ^{CDID}: durchschnittlicher Treatment-on-Treated Effekt nach Matching auf Basis des Conditional Difference-In-Differences Schätzers.

So berücksichtigt der Conditional Difference-In-Differences Schätzer unbeobachtete, lineare und zeitinvariate Effekte. Es ist nun möglich, zwischen einem zeitlichen Trend und unbeobachteter Heterogenität zu differenzieren.

Der durchschnittliche Wert für den Trendeffekt bei den Nicht-Teilnehmern an der Maßnahme ergibt sich hierbei in der folgenden Weise:

$$\text{(22)} \qquad E\left[Y^0_{j,t} - Y^0_{j,t'} \middle| P(X)\right] = \frac{1}{|I|} \sum_{i \in I} \sum_{j \in J} w_{i,j} \cdot \left(Y^0_{j,t} - Y^0_{j,t'}\right) \qquad t' < t_T < t$$

So entspricht das Counterfactual Outcome der Teilnehmer dem gewichteten Mittelwert der Differenzen der Werte der Ergebnisvariablen für die jeweiligen Matching-Partner.

4.4 Illustratives Beispiel

Aufbauend auf dem in Tabelle 2 dargestellten Zahlenbeispiel werden nun die unterschiedlichen Schätzer zur Bestimmung des durchschnittlichen Treatment-on-Treated Effekts anhand eines illustrativen Beispiels verdeutlicht. Das Zahlenbeispiel weist Beobachtungen von 9 Kunden auf, von denen 4 Kunden eine Kundenkarte besitzen. Als Störvariable wird das Haushaltsnettoeinkommen als kategoriale Variable berücksichtigt. Das Unternehmen möchte wissen, ob der Besitz der Kundenkarte dazu führt, dass Kunden mehr Umsatz bei dem Unternehmen tätigen. Es wird ein direktes Matching durchgeführt und es werden alle Nicht-Teilnehmer als Matching-Partner berücksichtigt. Zudem wird der Nearest Neighbor Algorithmus mit Zurücklegen angewendet.

Tabelle 2: Zahlenbeispiel zur Schätzung des Effekts des Besitzes der Kundenkarte auf den getätigten monatlichen Umsatz

Kunde	Haushaltsnetto-einkommen	Besitz der Kundenkarte	Umsatz des Kunden je Monat **vor** Einführung der Kundenkarte	Umsatz des Kunden je Monat **nach** Einführung der Kundenkarte
1	2.000 € und mehr	Ja	140 €	177 €
2	2.000 € und mehr	Ja	130 €	167 €
3	2.000 € und mehr	Nein	140 €	152 €
4	1.500 € - 1.999 €	Ja	30 €	65 €
5	1.000 € - 1.499 €	Ja	40 €	75 €
6	1.500 € - 1.999 €	Nein	30 €	40 €
7	1.000 € - 1.499 €	Nein	40 €	50 €
8	500 € - 999 €	Nein	30 €	40 €
9	500 € - 999 €	Nein	40 €	50 €

Dem Unternehmen liegen die in Tabelle 2 dargestellten Informationen vor und nach der Einführung der Kundenkarte vor. Der Vergleich der Mittelwerte zwischen den beiden Gruppen der Besitzer einer Kundenkarte und der Nicht-Besitzer nach Einführung der Kundenkarte ergibt einen Unterschied bezüglich des monatlichen Umsatzes von 54,60 € (siehe Tabelle 3).

Tabelle 3: Ergebnis des Mittelwertvergleichs

Durchschnittlicher Umsatz der Gruppe der Besitzer einer Kundenkarte (1, 2, 4, 5)	121,00 €
Durchschnittlicher Umsatz der Gruppe der Nicht-Besitzer einer Kundenkarte (3, 6, 7, 8, 9)	66,40 €
Differenz der Mittelwerte der beiden Gruppen	54,60 €

Dieser Mittelwertunterschied kann durch den Besitz der Kundenkarte, aber auch durch Selbstselektion der Kunden bedingt sein. Aus diesem Grund wird im Folgenden die Matching Methode angewendet. Bei dieser erfolgt ein direktes Matching auf Basis der Variable Haushaltsnettoeinkommen, da vermutet wird, dass das Haushaltsnettoeinkommen (Störvariable) aufgrund der Konditionen der Kundenkarte deren Besitz beeinflusst. So werden dann die Kunden 1 und 2 mit 3 und die Kunden 4 und 5 mit 6 bzw. 7 verglichen. Die Berechnung des Matching-Schätzers führt zu dem in Tabelle 4 dargestellten Ergebnis.

Tabelle 4: Ergebnis des Matching-Schätzers

	Umsatz je Monat bei Besitz der Kundenkarte	Umsatz je Monat des Matching-Partners	Differenz
Kunde 1	177,00 €	152,00 €	25,00 €
Kunde 2	167,00 €	152,00 €	15,00 €
Kunde 4	65,00 €	40,00 €	25,00 €
Kunde 5	75,00 €	50,00 €	25,00 €
Mittelwert	121,00 €	98,50 €	22,50 €

Tabelle 4 zeigt, dass der Besitz der Kundenkarte bei den Kunden eine durchschnittliche Steigerung des monatlichen Umsatzes und damit einen durchschnittlichen Treatment-on-Treated Effekt in Höhe von 22,50 € hervorruft.

Bei Anwendung des Difference-In-Differences Schätzers wird nun die Veränderung des monatlichen Umsatzes der Kunden, die eine Kundenkarte besitzen, mit der Veränderung des monatlichen Umsatzes der Kunden ohne Kundenkarte betrachtet. Es zeigt sich bei den 4 Kunden mit Kundenkarte eine durchschnittliche Differenz des monatlichen Umsatzes vor und nach Einführung der Kundenkarte von 36,00 €. Bei den Kunden ohne Kundenkarte ergibt sich hingegen eine durchschnittliche Differenz von 10,40 €, so dass ein Trendeffekt angenommen werden kann. Der durchschnittliche Effekt des Besitzes der Kundenkarte auf den monatlichen Umsatz beträgt somit 25,60 €.

Tabelle 5: Ergebnis des Difference-In-Differences Schätzer

Durchschnittliche Differenz des Umsatzes je Monat der Kunden **mit** Kundenkarte	Durchschnittliche Differenz des Umsatzes je Monat der Kunden **ohne** Kundenkarte	Durchschnittlicher Effekt des Besitzes der Kundenkarte auf den Umsatz je Monat
36,00 €	10,40 €	25,60 €

Bei Anwendung des Conditional Difference-In-Differences Schätzers erfolgt nun eine Kombination des Matching-Schätzers und des Difference-In-Differences Schätzers (Tabelle 6).

Tabelle 6: Ergebnis des Conditional Difference-In-Differences Schätzer

	Differenz des Umsatzes je Monat der Kunden **mit** Kundenkarte	Differenz des Umsatzes je Monat der Matching-Partner	Differenz
Kunde 1	37,00 €	12,00 €	25,00 €
Kunde 2	37,00 €	12,00 €	25,00 €
Kunde 4	35,00 €	10,00 €	25,00 €
Kunde 5	35,00 €	10,00 €	25,00 €
Mittelwert	36,00 €	11,00 €	25,00 €

Tabelle 6 zeigt, dass in beiden Gruppen (Besitzer und Nicht-Besitzer der Kundenkarte) nun ein Effekt der Teilnahme an der Maßnahme von 25,00 € ermittelt wird. Zudem liegt ein Trendeffekt von 12,00 € für die Haushalte mit einem hohen Haushaltsnetteinkommen und von 10,00 € für Haushalte mit einem geringen Haushaltsnetteinkommen vor. So ist es bei Anwendung des Conditional Difference-In-Differences Schätzers im Gegensatz zum Difference-In-Differences Schätzer möglich, Heterogenität in den Trendeffekten aufzudecken.

Daher ergibt sich bei Betrachtung des ursprünglichen Mittelwertvergleichs, dass 54,21% des beobachteten Effekts auf einen Selbstselektionseffekt und 45,79% auf den durchschnittlichen Treatment-on-Treated Effekt zurückzuführen sind (siehe Tabelle 7).

Tabelle 7: Aufspaltung des gesamten Effekts in den durchschnittlichen Treatment-on-Treated Effekt und Selbstselektionseffekt

Differenz der Mittelwerte vor Matching	Treatment-on-Treated Effekt bei Anwendung des CDID Schätzers	Selbstselektionseffekt bei Anwendung des CDID Schätzers
54,60 € (100%)	25,00 € (45,79%)	29,60 € (54,21%%)

4.5 Vergleich der Schätzer zur Ermittlung des durchschnittlichen Treatment-on-Treated Effekts

Abschließend erfolgt nun ein Vergleich der unterschiedlichen Schätzer, wobei hierfür die folgenden Kriterien herangezogen werden:

- **Anforderungen an die Daten**: Die vorgestellten Schätzer stellen unterschiedliche Anforderungen an die benötigten Daten. In der Praxis liegen häufig nur bestimmte Daten vor. Aus diesem Grund wird der Trade-Off zwischen der Menge an verfügbaren Daten und dem Erkenntnisgewinn bezüglich des durchschnittlichen Treatment-on-Treated Effekts diskutiert.

- **Berücksichtigte Effekte**: Aufgrund des fundamentalen Evaluierungsproblems kann der wahre durchschnittliche Treatment-on-Treated Effekt nur näherungsweise bestimmt werden. Hierfür ist es erforderlich, dass der geschätzte durchschnittliche Treatment-on-Treated Effekt unverzerrt ermittelt wird. Aus diesem Grund werden die betrachteten Schätzer hinsichtlich ihrer Annahmen und deren Implikationen für eine Evaluierung des durchschnittlichen Treatment-on-Treated Effekts diskutiert. Hierfür werden die Effekte herangezogen, die durch die Schätzer berücksichtigt werden.

Um den **Matching-Schätzer** ermitteln zu können, sind lediglich Querschnittsdaten für einen Zeitpunkt erforderlich. Dementsprechend stellt der Matching-Schätzer geringe Anforderungen an die erforderlichen Daten. Diese geringen Datenanforderungen führen jedoch dazu, dass nur eine statische Betrachtung des durchschnittlichen Treatment-on-Treated Effekts erfolgt. Ist zu vermuten, dass ein Trend existiert, so kann dieser auf Basis des Matching-Schätzers nicht ermittelt werden. Auch erfasst der Matching-Schätzer lediglich die beobachtete Heterogenität, die durch die Störvariablen berücksichtigt wird. Für eine adäquate Ermittlung des durchschnittlichen Treatment-on-Treated Effekts ist es allerdings erforderlich, dass alle relevanten Störvariablen für die Bestimmung der Partner von Teilnehmern und Nicht-Teilnehmern der Maßnahme berücksichtigt werden. Ist dies nicht gewährleistet, so kann der Matching-Schätzer aufgrund unbeobachteter Heterogenität verzerrt sein, so dass der wahre durchschnittliche Treatment-on-Treated Effekt überschätzt oder unterschätzt wird. So bleibt festzuhalten, dass der Matching-Schätzer überhaupt nur dann den wahren durchschnittlichen Treatment-on-Treated Effekt abbilden kann, wenn Trends nicht von Bedeutung sind und keine unbeobachtete Heterogenität vorliegt.

Zur Berechnung des **Difference-In-Differences Schätzers** ist es erforderlich, dass gepoolte Daten, die zu zwei Zeitpunkten erhoben werden, vorliegen. Dabei ist relevant, dass die Gruppe der Teilnehmer an der Maßnahme zum ersten Beobachtungszeitpunkt noch nicht an der Maßnahme teilgenommen hat, so dass $Y^0_{i,t'}$ beobachtet werden kann. Aufgrund dieser Voraussetzung stellt die Ermittlung des Difference-In-Differences Schätzers höhere Anforderungen an die Daten als der Matching-Schätzer. Bezüglich der adäquaten Bestimmung des durchschnittlichen Treatment-on-Treated Effekts ist festzuhalten, dass der Difference-In-Differences Schätzer in der Lage ist, mögliche Trendeffekte zu berücksichtigen. Zu einer verzerrten Evaluierung des durchschnittlichen Treatment-on-Treated Effekts kann es jedoch kommen, wenn Heterogenität in den Trendeffekten existiert und wenn die zukünftigen Teilnehmer einer Maßnahme ihre Teilnahme antizipieren und daraufhin ihr Verhalten bereits vor der Teilnahme an der Maßnahme ändern (Fitzenberger & Speckesser 2001, S. 11).

Um den **Conditional Difference-In-Differences Schätzer** ermitteln zu können, sind ebenfalls gepoolte Daten, die zu zwei Zeitpunkten erhoben werden, erforderlich. Dabei ist ebenfalls relevant, dass die Gruppe der Teilnehmer an der Maßnahme zum ersten Beobachtungszeitpunkt noch nicht an der Maßnahme teilgenommen hat, so dass $Y^0_{i,t'}$ beobachtet werden kann. Aufgrund dieser Voraussetzung stellt die Schätzung des Conditional Difference-In-Differences Schätzers höhere Anforderungen an die Daten als der Matching-Schätzer. Bei Anwendung des Conditional Difference-In-Differences Schätzers wird wie auch bei dem Difference-In-Differences Schätzer ein möglicher Trendeffekt berücksichtigt. Jedoch ist es bei Anwendung des Conditional Difference-In-Differences Schätzers zudem möglich, unterschiedliche Trendeffekte für die Teilnehmer und Nicht-Teilnehmer an der Maßnahme zu evaluieren. So kann der unbeobachteten Heterogenität in Abhängigkeit von den beobachteten Störvariablen Rechnung getragen werden. In der Tabelle 8 wird der Vergleich der unterschiedlichen Schätzer zusammengefasst.

Tabelle 8: Vergleich der unterschiedlichen Schätzer

	Anforderung an die Daten	Berücksichtigte Effekte
Matching-Schätzer	- Erhebung der Ergebnisvariablen und jener Variablen, die für das Matching herangezogen werden sollen - Querschnittsdaten für einen Zeitpunkt	- Selbstselektionseffekt basiert auf beobachteter Heterogenität - Mögliche Trendeffekte werden nicht berücksichtigt
Difference-In-Differences Schätzer	- Erhebung der Ergebnisvariablen - Gepoolte Daten, die mindestens zu zwei Zeitpunkten erhoben wurden	- Selbstselektionseffekt basiert auf Bildung der Differenzen - Mögliche Trendeffekte können berücksichtigt werden
Conditional Difference-In-Differences Schätzer	- Erhebung der Ergebnisvariablen und jener Variablen, die für das Matching herangezogen werden sollen - Gepoolte Daten, die mindestens zu zwei Zeitpunkten erhoben wurden	- Selbstselektionseffekt basiert auf beobachteter Heterogenität - Unbeobachtete Heterogenität in den Trendeffekten wird berücksichtigt - Mögliche Trendeffekte können berücksichtigt werden

5 Fazit

Dieser Beitrag zeigte auf, wie mit Hilfe der Matching Methode Selbstselektionseffekte berücksichtigt werden können. Die angemessene Berücksichtigung von Selbstselektionseffekten ist immer dann von Bedeutung, wenn nicht nur ein Unterschied zwischen zwei Gruppen festgestellt, sondern auch Rückschlüsse auf eine kausale Beziehung gezogen werden sollen. So gibt es in der Betriebswirtschaft zahlreiche Fragestellungen, bei denen der Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable von Interesse ist. Es sei aber darauf hingewiesen, dass für eine Prognose die Matching Methode nicht angewendet werden muss (Cox & Wermuth 2004).

Gezeigt wurde, wie der Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable angemessen ermittelt werden kann. Dabei wurden unterschiedliche Varianten der Matching Methode dargestellt. Da Barabas (2004) gezeigt hat, dass unterschiedliche Spezifikationen stabile Ergebnisse bei der Evaluierung des durchschnittlichen Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable liefern, ist die Matching Methode in einfacher Weise anwendbar. Voraussetzung für die angemessene Evaluierung des Effekts der Teilnahme an einer Maßnahme auf eine Ergebnisvariable ist jedoch, dass alle relevanten Störvariablen erfasst werden.

Es stellt sich aber die Frage, ob nicht eine einfache Regressionsanalyse ebenfalls in der Lage ist, den Effekt der Teilnahme an einer Maßnahme auf die Ergebnisvariable zu evaluieren. Das Berücksichtigen der Teilnahmeentscheidung, beispielsweise in Form einer Dummy-Variable, sowie der Störvariablen als unabhängige Variablen führt allerdings dazu, dass der Effekt der Teilnahme verzerrt geschätzt wird. Dies liegt darin begründet, dass die Störvariablen sowohl einen Einfluss auf die Teilnahmeentscheidung als auch auf die Ergebnisvariable haben. Es liegt dann eine Verzerrung aufgrund des Vorliegens endogener Variablen vor. In dem Beispiel ergibt sich bei einer Berücksichtigung des Besitzes der Kundenkarte sowie des Einkommens als unabhängige Variable und dem monatlichen Umsatz des Kunden als abhängige Variable ein Effekt des Besitzes der Kundenkarte von 23,00 €. Auch dieser geschätzte Effekt entspricht nicht dem wahren Effekt des Besitzes der Kundenkarte, da der Endogenität nicht angemessen Rechnung getragen wurde. So beeinflusst das Einkommen sowohl die Teilnahmeentscheidung als auch die Höhe des monatlichen Umsatzes eines Kunden.

Eine Annahme der Regressionsanalyse ist, dass keine Korrelation zwischen den unabhängigen Variablen und dem Fehlerterm existiert. Wenn jedoch eine Korrelation besteht, so sind die geschätzten Koeffizienten verzerrt und es liegen dann endogene Variablen vor. In der

Literatur wird daher der Instrumental Variable Ansatz diskutiert, um dem Problem endogener Variablen Rechnung zu tragen (Wooldridge 2003). So wird im Instrumental Variable Ansatz ebenfalls der Effekt von unabhängigen Variablen auf die Ergebnisvariable anhand eines Regressionsmodells formuliert. Jedoch gilt es, für die endogenen Variablen so genannte Instrumente zu finden, die mit den entsprechenden endogenen Variablen korrelieren, nicht aber mit dem Fehlerterm der Regressionsgleichung, die den Wert der Ergebnisvariablen erklärt. Eine zweistufige Schätzung ermöglicht dann eine adäquate Evaluierung des Effekts der Teilnahme an einer Maßnahme, da zunächst in einem ersten Schritt der Einfluss des Instruments auf die endogene Variable – hier die Teilnahme an einer Maßnahme – spezifiziert wird. In einem zweiten Schritt wird dann der Effekt der Teilnahme an einer Maßnahme auf die Ergebnisvariable unverzerrt geschätzt. Der Instrumental Variable Ansatz wurde bereits bei einigen betriebswirtschaftlichen Fragestellungen angewendet, um Selbstselektionseffekte zu berücksichtigen (Erdem, Keane, & Sun 1999; Zettelmeyer, Morton, & Silvia-Risso 2003). In betriebswirtschaftlichen Anwendungen ist es jedoch häufig schwierig, Instrumente zu finden, die die oben beschriebene Eigenschaft besitzen. Die Matching Methode vermeidet die Identifizierung solcher Instrumente. Jedoch liegt ihr die zentrale Annahme zugrunde, dass alle relevanten Störvariablen als Kontrollvariablen erfasst wurden (Heckman & Navarro-Lozano 2004).

Weitere Ansätze, die sich mit kausalen Effekten beschäftigen sind beispielsweise Graphenmodelle, die eine Kombination aus Wahrscheinlichkeitstheorie und Graphentheorie repräsentieren (Lauritzen 1999; Edwards 2000). Hierzu zählen beispielsweise Bayesianische Netzwerke. Das Ziel dieser Modelle besteht jedoch in erster Linie nicht darin, den Effekt der Teilnahme an einer Maßnahme auf eine Ergebnisvariable zu evaluieren, sondern primär kausale Zusammenhänge abzubilden.

Abschließend ist anzumerken, dass die Berücksichtigung von Selbstselektionseffekten in der Zukunft eine bedeutendere Stellung in der betriebswirtschaftlichen Forschung einnehmen wird. Diese Einschätzung wird primär von der Entwicklung getragen, dass aufgrund der vermehrten Diskussion von Selbstselektionseffekten in der volkswirtschaftlichen Literatur auch in der betriebswirtschaftlichen Literatur das Problembewusstsein geschärft wird. Dies wird beispielsweise auch an der breiten Diskussion über Endogenität in betriebswirtschaftlichen Modellen deutlich. Somit ist davon auszugehen, dass die Diskussion über adäquate Methoden zur Berücksichtung von Selbstselektion in betriebswirtschaftlichen Fragestellungen weiter an Bedeutung gewinnen wird.

6 Literatur

Ashenfelter, O. (1978). Estimating the Effect of Training Programs on Earnings. *The Review of Econometrics and Statistics*, 60, 47-57.

Ashenfelter, O., & Rouse, C. (1998). Income, Schooling, and Ability: Evidence from a New Sample of Identical Twins. *The Quarterly Journal of Economics*, 253-284.

Barabas, J. (2004). How Deliberation Affects Policy Opinions. *American Political Science Review*, 98, 1-16.

Bjorklund, A., & Moffitt, R. (1987). The Estimation of Wage Gains and Welfare Gains in Self-Selection Models. *The Review of Economics and Statistics*, 69, 42-49.

Black, D., & Smith, J. (2004). How Robust Is the Evidence On the Effects of College Quality? Evidence from Matching. *Journal of Econometrics*, 121, 99-124.

Bortz, J. (1999). *Statistik für Sozialwissenschaftler*. Berlin et al.: Springer.

Bundesanstalt für Arbeit (2003). *138 Milliarden Euro für aktive Arbeitsmarktpolitik im Osten*. Retrieved 1. November, from http://www.soliserv.de/presse-arbeitsamt_2quartal-03.htm.

Christensen, B., Clement, M., Albers, S., & Guldner, S. (2004). *Zur Relevanz der Kontrollgruppenauswahl in der Empirischen Forschung: Eine Analyse am Beispiel der Erfolgswirkung der Academy Awards im Filmgeschäft*. Working Paper, Christian-Albrechts-Universität zu Kiel, Kiel.

Cox, D. F., & Wermuth, N. (2004). Causality: A Statistical View. *International Statistical Review*, 72, 285-305.

D'Agostino, R. B. (1998). Tutorial in Biostatics: Propensity Score Methods for Bias Reduction in the Comparison of a Treatment to a Non-Randomized Control Group. *Statistics in Medicine*, 17, 2265-2281.

Degeratu, A., Rangaswamy, A., & Wu, J. (2000). Consumer Choice Behaviour in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes. *International Journal of Research in Marketing*, 17, 55-78.

Dehejia, R. H., & Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics*, 84, 151-161.

Edwards, D. (2000). *Introduction to Graphical Modelling*. Berlin: Springer.

Erdem, T., Keane, M., & Sun, B. (1999). Missing Price and Coupon Availability Data in Scanner Panels: Correcting for the Self-Selection Bias in the Choice Model Parameters. *Journal of Econometrics*, 89, 177-196.

Fitzenberger, B., & Speckesser, S. (2001). *Weiterbildungsmaßnahmen in Ostdeutschland: Ein Misserfolg der Arbeitsmarktpolitik?* White Paper: ZEW Discussion Paper.

Granger, C. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37, 424-438.

Heckman, J. (1976). The Common Structure Of Statistical Models Of Truncation, Sample Selection, And Limited Dependent Variables And A Simple Estimator For Such Models. *Annals of Economic and Social Measurement*, 5, 475-492.

Heckman, J. (1978). Dummy Endogenous Variables in a Simultaneous Equations System. *Econometrica*, 46, 931-960.

Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47, 152-162.

Heckman, J., Ichimura, H., Smith, A. K., & Todd, P. (1998). Characterizing Selection Bias Using Experimantal Data. *Econometrica*, 66, 1017-1098.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1996). Sources of Selection Bias in Evaluating Social Programs: An Interpretation of Conventional Measures and Evidence on the Effectiveness of Matching as a Program Evaluation Method. *Proceedings of the National Academy of Science*, 93, 13416-13420.

Heckman, J., Ichimura, H., & Todd, P. (1998). Matching as an Econometric Evaluation Estimator. *Review of economic Studies*, 65, 261-294.

Heckman, J., & Navarro-Lozano, S. (2004). Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models. *The Review of Economics and Statistics*, 86, 30-57.

Heckman, J. J., LaLonde, R. J., & Smith, J. A. (1999). The Economics and Econometrics of Active Labor Market Programs. In O. Ashenfelter, & D. Card (Eds.), *Handbook of Labor Economics* (pp. 1865–2097). Amsterdam: North Holland.

Hitt, L. M., & Frei, F. X. (2002). Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking. *Management Science*, 48, 732-748.

Hujer, R., Caliendo, M., & Radic, D. (2001). *Nobody Knows... How do different Evaluation Estimators Perform in a Simulated Labour Market Experiment?* Working Paper, Johann Wolfgang Goethe-Universität, Frankfurt.

Hujer, R., Caliendo, M., & Radic, D. (2003). *Methods and Limitations of Evaluation and Impact Research*. Working Paper, Johann Wolfgang Goethe-University, Frankfurt.

Hujer, R., Maurer, K.-O., & Wellner, M. (1997). *The Impact of Training on Unemployment Duration in West Germany: Combining a Discrete Hazard Rate Model with Matching Techniques*. Working Paper, Johann Wolfgang Goethe-Universität, Frankfurt.

Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *Review of Economics and Statistics*, 86, 4-29.

LaLonde, R. J. (1986). Evaluating the Econometric Evaluations of Training Programs with Experimental Data. *The American Economic Review*, 76, 604-620.

Lauritzen, S. (1999). *Causal Inference from Graphical Models*. Working Paper, Aalborg University, Aalborg.

Lechner, M. (1998). *Training the East German Labour Force*. Heidelberg: Physica.

Lechner, M. (2002). Program Heterogeneity and Propensity Score Matching: An Application to the Evaluation of Active Labor Market Policies. *Review of Economics and Statistics*, 84, 205-220.

Lee, L.-f. (2000). Self-Selection. In B. Baltagi (Ed.), *A Companion to Theoretical Econometrics* (pp. 383-409). Malden: Blackwell.

Rasch, S., & Lintner, A. (2001). *The Multichannel Consumer: The Need To Integrate Online and Offline Channels In Europe*. White Paper, Boston: Boston Consulting Group.

Rässler, S. (2002). *Statistical Matching*. New York et al.: Springer.

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70, 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group using Multivariate Matched Sampling Methods that incorporate the Propensity Score. *The American Statistician*, 39, 33-38.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers*, 3, 135-146.

Rubin, D. (1990). Comment on “Neyman (1923) and Causal Inference in Experiments and Observational Studies”. *Statistical Science*, 5, 472-480.

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, 66, 688-701.

Singer, B. (1986). Self-Selection and Performance-Based Ratings: A Case Study in Program Evaluation. In H. Wainer (Ed.), *Drawing Inference from Self-Selected Samples* (pp. 29-62).

Smith, J., & Todd, P. (2000). *Does Matching Overcome Lalondes Critique of Nonexperimental Estimators?* White Paper: Penn Institute for Economic Research.

Wehrling, R. (2002). Retail E-Banking: Tinkering Pays Off. *ABA Banking Journal*, 11-23.

Wooldridge, J. M. (2003). *Introductory Econometrics: A Modern Approach*. Mason: Thomson South West.

Zettelmeyer, F., Morton, F. S., & Silvia-Risso, J. (2003). *Cowboys or Cowards: Why are Internet Car Prices Lower?* Working Paper, National Bureau of Economic Research, Cambridge.

Beitrag 2

Effect of Channel Use on Customer Profitability

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Eingereicht zum

Journal of Marketing Research

Mai 2006

Effect of Channel Use on Customer Profitability

Abstract

To successfully manage multiple channels, managers need to know which channel contributes to what extent to individual customer profitability. Given that customers select a specific channel, we have to disentangle treatment and selection effects. We propose the hybrid matching method to estimate the treatment effect of channel use on customer profitability and develop a model to decompose this effect into its quantity and profitability components. The results of an empirical study - where we use information on about 200,000 customers of a large European retail bank - illustrate that decomposition into treatment and selection effects is crucial and show that online customers are in most cases more profitable than offline customers. We also compare the hybrid matching method with regression methods and find a higher predictive validity for the hybrid matching method. Moreover, we assess the impact of customer channel migration activities on individual customer profitability and demonstrate that migrating customers to the online channel may lead to a 15 percent increase in aggregate customer profitability.

Keywords: Selection Effects, Matching Method, Customer Channel Migration

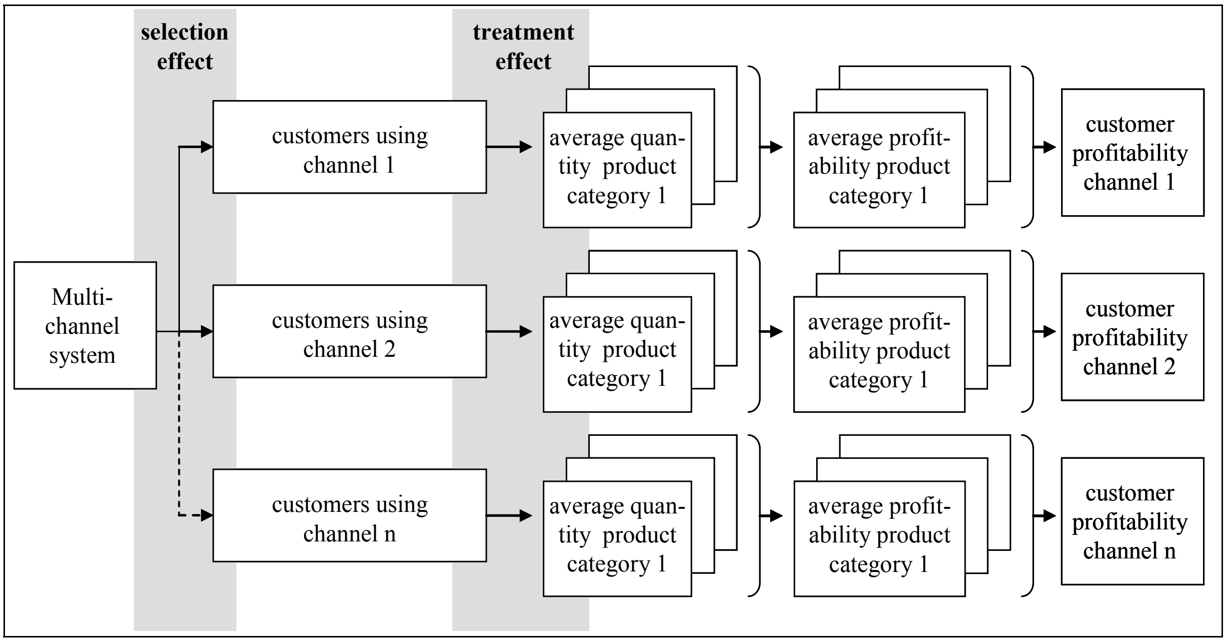
1 Introduction

Distribution channels are an integral part of a firm's customer management strategy that aims to enhance the profitability of its customers. Hence, managers need to know which channel contributes to what extent to individual customer profitability. Differences in a channel's contribution to customer profitability might be due to channel costs and channel returns (Malone, Yates, & Benjamin 1987). For example, the perceived convenience of a channel and additional customer information provided by a distribution channel might support incremental product purchase (Hitt & Frei 2002). If distribution channels have an impact on customer profitability, they offer managers the opportunity to improve their firm's performance by actively managing customer channel migration (Ansari, Mela, & Neslin 2005; Thomas & Sullivan 2005). Currently, most managers assume that customers using the online channel (online customers) are more profitable than offline customers. The Bank of America states, for example, that the company's 12.6 million online customers are 27 percent more profitable than their offline counterparts (Europress Publications 2005).

Yet to properly evaluate the impact of a channel on customer profitability, managers need to determine the treatment effect which is the result of a change in customer behavior due to the use of a particular channel. This change in customer behavior will result in a change in customer profitability. However, a simple mean comparison of the profitability of customers using a particular channel with customers who are not using that channel might be biased due to selection effects. Those effects exist because customers select themselves into a channel and customers are likely to be systematically distinct across channels with respect to their customer characteristics. For instance, some studies find that online customers are more affluent than offline customers (e.g. Degeratu, Rangaswamy, & Wu 2000; Shankar, Smith, & Rangaswamy 2003). Hence, treatment and selection effects have to be disentangled to determine the effect of channel use on customer profitability. The estimation of the treatment effect for every customer then describes the individual effects of customer channel migration activities (Ansari, Mela, & Neslin 2005).

The outcomes of this study emphasize that customer profitability has to be disentangled into treatment and selection effects and that the hybrid matching method is a suitable method to do so. Even more detailed conclusions for evaluating customer channel migration activities can be derived by decomposing customer profitability into its profitability and quantity components (see Figure 1). The monetary consequences of treatment and selection effects can be evaluated in detail and customers for whom channel migration has positive profitability implications can be identified.

Figure 1 Conceptual framework



The quantity components of customer profitability describe the average quantities demanded of a specific product category by the customers using a particular channel. For instance, in a traditional retail setting the quantity components are the average sales in a product category. In retail banking the quantity components are the number of products, the balances of the different accounts as well as the number of transactions. Multiplying the quantity components with their margins or unit costs leads to the profitability components of customer profitability. These are the contribution margins and operating costs for a specific product category generated by customers using a particular channel. It is important to distinguish between quantity and profitability components, since distribution channels might have an effect on certain quantity components, but those effects might be marginal from a profitability perspective.

The aims of this paper are (i) to decompose the effect of channel use on customer profitability into treatment and selection effects for each quantity and profitability component of customer profitability, (ii) to assess the impact of customer channel migration activities on individual customer profitability, (iii) to derive strategic implications for customer channel migration, and (iv) to propose the hybrid matching method as a flexible decomposition approach to disentangling treatment and selection effects that is also superior to other methods.

In the next section, we describe approaches to determining treatment and selection effects. Then, we demonstrate how these effects can be disentangled by using the hybrid matching method. This is followed by a discussion as well as a comparison and validation of the results of our empirical study. We study the effect of online channel use on customer profitability for about 200,000 customers of a large European retail bank. We then evaluate customer channel migration activities using the results of the empirical study. Finally, we summarize the results and derive conclusions.

2 Approaches to Determine Treatment and Selection Effects

Instrumental Variables (IV) methods and Matching methods are the two most prominent approaches to disentangling treatment and selection effects (Wooldridge 2002, p. 603). Both approaches are based on the idea that an individual may occupy two potential states (Roy 1951; Rubin 1974). At any time an individual is either in the treated or untreated state but cannot be in both states at the same time. A fundamental evaluation problem occurs, because the outcome is observable in only one state, whereas the counterfactual outcome is unobservable .

(i) The Instrumental Variables (IV) method is a two stage approach (Little 1985). The first stage describes the relationship between the outcome variable of interest as the dependent and the treatment variable and other variables as the independent variables (outcome equation). In the case of unobserved variables that are correlated with the treatment variable and the outcome variable, the treatment variable is endogenous. In the second stage the treatment variable is a function of the instruments (selection equation) (Heckman 1974; Heckman 1976; Amemiya 1984).

The IV method requires the specification of a functional form and the identification of strong instruments: instrumental variables that are highly correlated with the treatment variable, but are uncorrelated with the error term in the outcome equation. When no strong instruments are present, applying the IV method might result in large asymptotic biases (Wooldridge 2003, p. 493). In marketing the IV method has rarely been applied to account for selection effects. Notable exceptions are Leenheer et al. (2004), who evaluate the effect of loyalty programs on customer behavioral loyalty; Zettelmeyer, Morton, & Silvia-Risso (2003), who evaluate the effect of using an online referral system on price, and Degeratu, Rangaswamy, & Wu (2000) who evaluate the effect of online channel use on customer loyalty.

(ii) In the absence of strong instruments, matching methods are alternative approaches to accounting for selection effects (Rosenbaum & Rubin 1983; Lee 2000). Unlike social experiments where all individuals are usually randomly assigned to groups of treated and untreated individuals, the matching method relies on a non-randomly chosen group of individuals being in the treated state (Dehejia & Wahba 1999). The matching method accounts for distorted sampling and rebuilds the design of an experimental study by building matched pairs of comparable treated and untreated individuals. Untreated individuals have to be similar to the treated individuals with respect to specific covariates. Covariates are observable variables that have both an impact on the outcome variable and on an individual's decision to participate in the treatment. Matching eliminates structural differences between the two groups, and hence the difference in the outcome variable can be attributed to the treatment (Dehejia & Wahba 2002). The outcome variable of the matched untreated individuals determines the counterfactual outcome for the treated individuals. The selection effect equals the difference between the total effect and the treatment effect.

In the literature several matching methods have been proposed: (1) matching on covariates, (2) propensity score matching, and (3) a hybrid approach that combines the basic ideas of propensity score matching and matching on covariates (Zhao 2004).

2.1 Matching on covariates

Matching on covariates builds matched samples by matching similar treated and untreated individuals based on a number of observable customer characteristics (covariates).

In the marketing literature, Shankar, Smith, & Rangaswamy (2003) and Hitt & Frei (2002) apply matching on covariates to account for differences between online and offline customers. Shankar, Smith, & Rangaswamy (2003) study online and offline customers in the lodging industry. They investigate whether levels of customer satisfaction and loyalty for the same service differ between customers who choose the service online versus those who choose the service offline. They consider sex, age, education, and income as covariates to build matched samples and identify that there are differences in customer satisfaction between online and offline customers even after accounting for selection effects.

Hitt & Frei (2002) compare the profitability of online and offline banking-customers. They consider online-banking use and customer characteristics simultaneously as independent variables in a regression model to evaluate whether online banking has an effect on customer profitability. However, this approach still results in biased estimates when selection effects are present. As customer characteristics show no significant effect in the regression model, they also use matched samples to check whether the customer characteristics' lack of explanatory power is a consequence of their assumed linear relationship between the customer characteristics and the outcome variables. Hitt & Frei (2002) use classes for continuous covariates (age and income) to reduce the problem of finding exact matching partners. However, they do not discuss the consequences of selection effects. Overall, they find that online customers are more profitable than offline customers. However, Hitt & Frei (2002) neither consider the quantity components of customer profitability nor take customer specific operating costs into account due to a lack of data. Moreover, Hitt & Frei (2002) determine solely whether online-banking use has an effect on customer profitability and they do not investigate the effects of customer channel migration activities on customer profitability.

Although matching on covariates is intuitively appealing, it might result in a problem of multidimensionality, when many covariates are considered to find exact matching partners. In particular, matching on covariates might fail when many of the considered covariates are continuous. Forming classes for the continuous covariates reduces the problem of finding exact matching partners. Yet Cochran (1968) shows that this approach might violate the assumption of covariate balance, which means that the covariates and the treatment variable are not conditionally independent within the matched samples.

2.2 Propensity score matching

Propensity score matching circumvents the violation of the assumption of covariate balance and avoids the formation of classes for continuous variables. Propensity score matching only considers one variable – the propensity score – to determine the matching partners. The propensity score summarizes the effect of different covariates and represents the conditional probability that an individual with a vector of observed covariates will be assigned to the treatment. The propensity score is estimated by a Logit or Probit model with the conditional probability as the dependent variable and the covariates as independent variables (Rosenbaum & Rubin 1983). Rosenbaum & Rubin (1983) demonstrate that propensity score matching leads to covariate balance and produces consistent estimates of the treatment effect. Identifying matching partners becomes only a one-dimensional problem which is the primary reason why propensity score matching is the matching method favored in economics (e.g. D'Agostino 1998; Hahn 1998; Lechner 1999; Dehejia & Wahba 2002; Black & Smith 2004; Dehejia 2005). However, it has never been applied in marketing.

2.3 Hybrid matching

Propensity score matching does not guarantee that the matched treated and untreated individuals are comparable with respect to their covariates. Therefore, hybrid matching matches treated and untreated individuals by considering the propensity score and specific covariates (Rosenbaum & Rubin 1985). Thus this approach is especially appropriate if there are a limited number of covariates that are closely linked to the outcome variable of interest (e.g. Lechner 1998).

In our empirical study, we do not observe strong instruments which can be applied to use the IV method. For that reason, we have to use matching methods. The hybrid matching method is in our case the most appropriate matching method because it combines the advantages of the propensity score matching and matching on covariates.

3 Hybrid Matching Method

3.1 Determining Matching Partners

In our empirical study, we investigate whether the use of the online channel has an effect on customer profitability. Hence, we need to estimate the counterfactual outcome for the online customers to evaluate treatment (effect of using the online channel) and selection effects. To this end, we have to determine the matching partners for every online customer. There are different algorithms that differ in the number of matching partners for a particular online customer (Heckman et al. 1998).

When there are many offline customers who are similar to an online customer it is appropriate to consider more than one matching partner to increase the reliability of the results. Considering more matching partners results in a smaller variance in the estimated outcome variable, but might induce some bias. The kernel algorithm considers all offline customers as matching partners and assigns a specific weight to every offline customer (Pagan & Ullah 1999, p. 23). The kernel algorithm requires one to specify the kernel function and the bandwidth parameter. The kernel function is a symmetric function around 0, typically a normal distribution. The bandwidth parameter controls the kurtosis of the kernel function. The smaller the bandwidth parameter, the more peaked the kernel function, and the larger the weight that is assigned to the nearest observation. We use the rule to determine the bandwidth parameter. It considers the standard deviation of the similarity measure as well as the sample size:

(1) $$\tau = 1.06 \cdot \sigma \cdot n^{-0.2}$$

where

τ = bandwidth parameter,
σ = standard deviation of similarity measure,
n = sample size.

We use the Mahalanobis distance to determine the similarity of online and offline customers (Abadie et al. 2001):

(2) $$w_{ij} = \frac{K\left(\frac{M_{ij}\left(P(X), x_c\right)}{\tau}\right)}{\sum_{j' \in J} K\left(\frac{M_{ij'}\left(P(X), x_c\right)}{\tau}\right)} \qquad \forall i \in I, j \in J$$

where

w_{ij} = weight of offline customer j for online customer i,
$K(\cdot)$ = kernel function that is normally distributed,
M_{ij} = Mahalanobis distance between online customer i and offline customer j,
P(X) = value of the propensity score,
x_c = vector of covariates.

Thus, all offline customers influence the counterfactual outcome of the online customers. However, offline customers with only a small Mahalanobis distance from a particular online customer get a high weight, those with a large distance a low weight.

3.2 Evaluating the Effect of Online-banking use on Customer Profitability

The outcome of the matched offline customers represents the counterfactual outcome of the online customers. Therefore the effect of online-banking use on the quantity components of customer profitability equals:

$$
(3) \qquad \begin{aligned}
\Delta_k^{TEAM} &= E\left[Y_{ik}^1 \middle| D=1, P(X), x_n\right] - E\left[Y_{ik}^0 \middle| D=1, P(X), x_n\right] \\
&= E\left[Y_{ik}^1 \middle| D=1, P(X), x_n\right] - E\left[Y_{jk}^0 \middle| D=0, P(X), x_n\right]
\end{aligned}
$$

where

Δ_k^{TEAM} = treatment effect after matching (TEAM) for quantity component k,

E [ ] = expected value,

$D = \begin{cases} 1 & \text{if customer uses the online channel,} \\ 0 & \text{otherwise.} \end{cases}$,

$Y_{ik}^1 \mid D=1$ = (observed) value of quantity component k for online customer i,

$Y_{ik}^0 \mid D=1$ = (unobserved) value of quantity component k for online customer i, if the customer did not use online banking,

$Y_{jk}^0 \mid D=0$ = (observed) value of quantity component k for offline customer j (j≠i).

The selection effect equals the difference between the total effect (mean difference between treated and untreated individuals) and the treatment effect (mean difference between the matched treated and untreated individuals).

4 Empirical Study

We use data from a large European retail bank. To disentangle treatment and selection effects we use information on about 200,000 customers, of which 1,707 customers are active online customers. We define a customer as an online customer when she makes more than one transaction online during the observation period. The observation period covers a three month period from July until September 2003. For validation purposes we also have information on those customers for another three month period from October until December 2002.

In Table 2 the quantity components of customer profitability that are relevant for customer profitability in retail banking are presented. The balances of checking accounts and savings accounts as well as the amount of private loans add up to the profitability component net interests received when multiplied by the net interest margins. The number of checking accounts, brokerage accounts, and credit cards as well as the turnover of brokerage accounts and credit cards determine the profit contribution from fees and commissions when considering the margins for fees and commissions. The average cross-selling rate of about 1.4 products indicates that quite a large proportion of customers holds just one product. Hence, the means for the number of checking accounts, brokerage accounts, and credit cards are quite small. The profitability component transaction costs results from the number of transactions in every channel, when channel specific costs are taken into account. The profitability component risk costs result from the risk of default and are determined by the retail bank based on specific customer characteristics.

Table 1 Mean values of online and offline customers

	Offline customers	Online customers	p-value
Age (years)	29.50	22.64	0.000
Length of relationship (month)	91.27	21.76	0.000
Joint account (dummy variable)	0.72	0.79	0.203
Number of products	1.44	1.41	0.018
Number of savings accounts	0.69	0.33	0.000

Table 1 shows the differences between online and offline customers in terms of age, length of relationship, whether the checking account is a joint account or not, number of different products, and number of savings accounts. We use those variables to estimate the propensity score, because they might also have an effect on customer profitability. Those variables turn out to be relevant, plausible and significant when estimating the propensity score. Moreover, we explicitly take age and length of relationship as covariates into account, since several studies show that those covariates especially affect the adoption of the online channel (e.g. Shankar, Smith, & Rangaswamy 2003; Kumar & Venkatesan 2005) as well as the profitability of customers (e. g. Hitt & Frei 2002). To avoid some customers having a disproportionately strong influence, we eliminate outliers by using the approach developed by Hadi (1994).

To test the reliability of the results regarding the direction and size of treatment and selection effects, we compare the results across 10 different sub-samples. We create those sub-samples by considering the 1,707 online customers and by randomly drawing 95,000 offline customers out of the roughly 200,000 offline customers observed.

5 Results of the Empirical Study

We separate the total differences in the quantity components of customer profitability into treatment and selection effects. To account for fluctuations in monthly values, we consider the average monthly values of the quantity components in the observed time span of 3 months.

Table 2 Rationales for the treatment effect

Quantity component of customer profitability	Rationale
Balance checking account	- online channel improves convenience of managing checking account - improved convenience allows customers to manage their assets more efficiently - due to managing their assets more efficiently online customers have more money at their disposal (Hitt & Frei 2002)
Balance savings account	- management of savings account is not possible using the online channel - savings account is characterized by low flexibility and restricted availability of money - efficient management of assets is hampered and leads to lower balances of savings accounts for online customers
Amount of private loan	- online channel improves convenience of raising a private loan - private loans are heavily promoted through online channel - online customers are to a greater extent exposed to product offers and product information (Hitt & Frei 2002) - online channel helps to overcome customer's inhibitions against borrowing money due to anonymity of online channel and leads to a larger amount of private loan for online customers
Number of checking accounts	- online channel improves convenience of using a checking account - online customers primarily use the online channel for managing their checking and brokerage account, and hence have a higher probability of acquiring a checking account
Number of brokerage accounts	- online channel improves convenience of using a brokerage account - online customers primarily use the online channel for managing their checking and brokerage account, and hence have a higher probability of acquiring a brokerage account - managing brokerage accounts through online channel causes lower costs
Turnover brokerage account	- online channel improves convenience of managing a brokerage account - online channel allows customers to react to a change in prices immediately - managing brokerage accounts using the online channel causes less costs
Number of credit cards	- customers manage their assets more efficiently (Hitt & Frei 2002) and hence they have a higher probability of acquiring a credit card
Turnover credit card	- due to managing their assets more efficiently online customers use credit cards more extensively (Hitt & Frei 2002)
Number of transactions	- online customers make more transactions due to improved convenience (Hitt & Frei 2002)

Literature regarding the effect of online-banking use on customer behavior, and hence the quantity components of customer profitability, is scarce. Moreover, there is no strong theory that allows us to derive hypotheses, but Table 2 summarizes rationales with respect to the treatment effect. We expect that online-banking use will have a positive effect on the balance of checking accounts, since checking accounts are flexible products that allow customers to manage their assets efficiently (Hitt & Frei 2002). Moreover, we suppose a positive effect of online-banking use on the number of checking accounts, because online banking is especially popular for managing checking accounts, and managing several checking accounts is very convenient using the online channel. In contrast, for the balance of savings account we expect a negative treatment effect, as savings can hardly be managed using the online channel. With this retail bank it is only possible to monitor the balances and to transfer money to the checking account. Furthermore, withdrawal of money is restricted, and thus prevents the efficient management of customers' assets.

Private loans have been heavily promoted on the online channel in recent years. In addition, online customers might overcome their inhibitions about borrowing money due to the perceived convenience and anonymity of the online channel. Hence we expect that online customers' amount of private loan will be higher.

The online channel improves the convenience of managing one's assets, which might lead to a higher turnover and a greater number of credit cards for online customers. Using credit cards also allows customers to manage their assets more efficiently. With respect to brokerage, we suppose that online-banking use will have a positive effect on the number of brokerage accounts, since managing brokerage accounts using the online channel is very convenient, popular, and cost efficient. In addition, we presume that online customers have a higher turnover of the brokerage account, because the online channel allows them to react to a change in prices immediately. The number of transactions might increase due to the improved convenience (Hitt & Frei 2002).

Table 3 Reliability of treatment effect (10 sub-samples)

	Mean	Significant treatment effect	Standard deviation	Coefficient of variation (absolute value)	Change of direction of effect
Balance checking account (€)	22.29	Yes	14.28	0.64	1
Balance savings account (€)	- 239.01	Yes	62.83	0.26	0
Amount of private loan (€)	2131.75	Yes	728.15	0.34	0
Number of checking accounts	0.04	Yes	0.00	0.05	0
Number of brokerage accounts	0.01	Yes	0.00	0.20	0
Turnover brokerage account (€)	- 58.40	No	130.77	2.24	5
Number of credit cards	0.01	Yes	0.00	0.40	1
Turnover credit card (€)	42.08	No	35.07	0.83	1
Number of transactions	2.64	Yes	0.05	0.02	0

Table 3 shows that the results for the estimated treatment effects are reliable for most quantity components, since the estimated treatment effect exhibits the same direction in most sub-samples and the standard deviation is small. Only the treatment effect for the turnover of the brokerage account is quite unstable: the estimated treatment effect has merely the same direction in half of the sub-samples. Furthermore, the coefficient of variation is also quite high (2.24). This results in an insignificant effect of online-banking use on the turnover of the brokerage account. Moreover, the effect of online-banking use on the turnover of credit cards is not significant.

Table 4 presents the results of the comparison of online and offline customers before and after matching. To determine the treatment and selection effect for the different quantity components, we use the mean values across the 10 sub-samples, whereas the size of the sub-samples depends on the considered quantity component of customer profitability. The total effect represents the difference in means between online and offline customers before matching (simple mean comparison). In contrast, the treatment effect is the difference in means between online and offline customers after matching. It measures the effect of online-banking use on the different quantity components. The selection effect equals the difference between the total effect and the treatment effect.

Contrary to the results before matching, after matching online-banking use has a positive effect on the balance of the checking account and the number of brokerage accounts. These results indicate that not accounting for selection effects might result in incorrect interpretations.

In addition, an over- or underestimation of the treatment effect can lead to incorrect strategic implications. That is the case for the balance of savings accounts and the number of checking accounts. The treatment effect is highly overstated when selection effects are not considered, since the treatment effect only accounts for about 30 percent of the total effect.

Our results indicate that online customers are more likely to have fewer assets, since we observe a negative selection effect for the balances of checking accounts and savings accounts as well as a positive selection effect for the amount of private loan. Online customers have a higher probability of purchasing loan products (number of credit cards) and have a tendency to hold flexible financial products (number of checking and brokerage accounts). Although the differences are only minor, the results indicate that using the online channel leads to an increasing acquisition of those products. Overall, those results are in line with the proposed rationales. The positive treatment effect for the number of transactions also supports the proposition that online customers conduct more transactions, since they manage their assets and liabilities more efficiently.

Table 4 Total effect, treatment effect and selection effect for the quantity components (monthly basis)

	N	Value of online customers – Value of offline customers* Total effect (p-value)	Treatment effect (p-value)	Selection effect
Balance checking account	20286	- 190.63 € (0.02)	22.29 € (0.00)	-212.92 €
Balance savings account	12041	- 870.87 € (0.00)	- 239.01 € (0.00)	-631.86 €
Amount of private loan	334	2777.33 € (0.03)	2131.75 € (0.01)	645.58 €
Number of checking accounts	25199	0.17 (0.00)	0.04 (0.00)	0.13
Number of brokerage accounts	25199	- 0.02 (0.00)	0.01 (0.00)	-0.03
Turnover brokerage account	904	- 44.61 € (n. s.)	-58.40 € (n.s.)	13.79 €
Number of credit cards	25199	0.016 (0.00)	0.01 (0.00)	0.011
Turnover credit card	713	53.18 € (n. s.)	42.08 € (n. s.)	11.09 €
Number of transactions	25199	3.47 (0.00)	2.64 (0.00)	0.83

* Values represent average values over the 10 sub-samples

We compute the values for the components of customer profitability on a monthly basis by using net interest margins, fees and commissions, and channel specific transaction costs as well as customer specific risk costs provided by the retail bank (see Table 5).

In general, using online banking has a positive effect on net interest received and this effect accounts for 86 percent of the total effect. This treatment effect is driven by the net interest received through private loans. Strong selection effects can be discerned when evaluating the effect of online-banking use on revenues from fees and commissions. The treatment effect only accounts for 33 percent of the total effect (0.82 € versus 0.28 €) and is overstated if one does not account for selection effects due to systematic differences between offline and online customers (see Table 1).

Table 5 Total effect, treatment effect and selection effect for the components of customer profitability (monthly basis)

	Value of online customers – Value of offline customers		
	Total effect (p-value)	Treatment effect (p-value)	Selection effect
Net interest received	**7.05 €**	**6.05 €**	**1.00 €**
Interest received checking account	-0.32 € (0.02)	0.03 € (0.00)	-0.35 €
Interest received savings account	-0.73 € (0.00)	-0.20 € (0.00)	-0.53 €
Interest received private loan	8.10 € (0.03)	6.22 € (0.01)	1.88 €
Fees and commissions	**0.82 €**	**0.28 €**	**0.54 €**
Fee checking account	0.51 € (0.00)	0.12 € (0.00)	0.39 €
Fee brokerage account	-0.03 € (0.00)	0.02 € (0.00)	-0.05 €
Commission turnover brokerage account	-0.22 € (n.s.)	-0.29 € (n.s.)	0.07 €
Fee credit card	0.03 € (0.00)	0.01 € (0.00)	0.02 €
Commission turnover credit card	0.53 € (n.s.)	0.42 € (n.s.)	0.11 €
Costs	**0.08 €**	**-0.06 €**	**0.14 €**
Transaction costs	-0.06 € (n.s.)	-0.07 € (n.s.)	0.01 €
Risk costs	0.14 € (0.00)	0.01 € (n.s.)	0.13 €

Taking channel specific transaction costs into account results in an insignificant effect of online-banking use on transaction costs (0.07 €). This is due to the fact that online customers still use other channels for their transactions and moreover conduct more transactions. Therefore, the managers' expectations of a significant decrease in transaction costs by migrating customers to the online channel are not realized (Myers, Pickersgill, & Van Metre 2004). Regarding risk costs, the results show that the treatment effect only accounts for 5 percent of the total effect, meaning that customers who have a higher risk for the retail bank prefer to use the online channel. However, this treatment effect is not significant. Hence, using online banking has no significant effect on customer specific costs.

Overall, decomposing the difference in monthly customer profitability between online and offline customers results in a treatment effect that accounts for 82 percent of the total effect and equals 6.39 € (6.05 € + 0.28 € - (-0.06 €)). This effect is observed when a customer holds every product. Since the average cross-selling rate is quite small, the individual effect on customer profitability is smaller and can even be negative. This finding confirms the results of who also find a positive effect of online-banking use on customer profitability. Yet they do not state the size of the effect and do not distinguish between treatment and selection effects which limits their ability to derive implications for customer channel migration.

6 Comparison with Regression Analysis and Validation of the Estimated Treatment Effects

We compare the outcomes of the hybrid matching method with the corresponding outcomes of a regression analysis (see Table 6). To some degree multiple regression analysis can alleviate selection effects when variables that are correlated with the treatment variable are included in the multiple regression equation (Wooldridge 2003, p. 247). Hence, we run a regression analysis with the covariates that we used to estimate the propensity score and a dummy variable that indicates whether a customer is an online customer or not as independent variables and the quantity components as dependent variables.

Table 6 Parameter estimates for the regression models (p-value in brackets)

	Constant	Online	Age	LOR[1)]	Joint account	Number of products	Number of savings
Balance checking account (R^2=0.04)	21.02 (0.445)	119.53 (0.000)	35.29 (0.000)	2.14 (0.000)	328.61 (0.000)	-178.83 (0.000)	-44.81 (0.000)
Balance savings account (R^2=0.06)	1415.02 (0.000)	-168.74 (0.016)	56.72 (0.000)	-2.52 (0.000)	904.99 (0.000)	-815.74 (0.000)	310.48 (0.000)
Amount private loan (R^2=0.07)	7998.65 (0.000)	1923.34 (0.000)	28.63 (0.021)	-11.46 (0.000)	3046.48 (0.000)	-162.77 (0.370)	-159.72 (0.348)
Number of checking accounts (R^2=0.35)	0.49 (0.000)	0.10 (0.000)	0.00 (0.000)	0.00 (0.000)	-0.04 (0.000)	0.38 (0.000)	-0.26 (0.000)
Number of brokerage accounts (R^2=0.03)	-0.03 (0.000)	-0.00 (0.361)	0.00 (0.222)	0.00 (0.000)	-0.02 (0.000)	0.03 (0.000)	0.02 (0.000)
Turnover brokerage account (R^2=0.00)	-2.17 (0.971)	-81.87 (0.262)	6.90 (0.000)	-0.42 (0.014)	103.94 (0.250)	2.44 (0.917)	10.99 (0.366)
Number of credit cards (R^2=0.32)	-0.25 (0.000)	0.00 (0.002)	0.00 (0.000)	0.00 (0.000)	0.04 (0.000)	0.22 (0.000)	-0.06 (0.000)
Turnover credit card (R^2=0.02)	-168.47 (0.000)	-28.51 (0.052)	3.52 (0.000)	0.09 (0.081)	19.07 (0.157)	18.85 (0.036)	33.41 (0.000)
Number of transactions (R^2=0.15)	10.07 (0.000)	8.24 (0.000)	-0.14 (0.000)	-0.00 (0.000)	4.02 (0.000)	7.77 (0.000)	-3.28 (0.000)

1) Length of relationship

Using the online channel has a significant negative effect on the balance of savings accounts and turnover credit card. A positive significant effect of using the online channel occurs for the balance of checking accounts, number of checking accounts, number of credit cards, amount of private loan, and number of transactions. Whereas the effect of using the online channel on the number of brokerage accounts is not significant in the regression model, it is significant and positive when using the hybrid matching method. While the direction of the estimated treatment effects in the regression model and the hybrid matching method correspond, the size of the estimated treatment effects differ. Moreover, in a regression model it is not easily possible to determine selection effects.

To compare the predictive validity of both models, we use the data of customers who went online between November and December 2002. For those 157 customers we observe their quantity components when they were offline. All of those customers hold a checking account, but only a limited number of other product categories. For that reason, we are only able to compare the predictive validity for the quantity components balance checking account and number of checking accounts.

As a benchmark we consider the observed difference in the quantity components before and after those customers went online. The observed effect for the balance of checking accounts and number of checking accounts is 5.97 percent and 2.62 percent, respectively. The estimated treatment effect on the two quantity components equals 3.11 percent and 4.46 percent when applying the hybrid matching method. The corresponding estimates are 11.39 percent and 13.70 percent for the regression analyses. The regression analyses strongly overestimate the treatment effect, while the estimates based on the hybrid matching approach are much closer to the observed values.

To further validate this result, we compute the mean absolute error (MAE) with respect to the observed difference in the quantity components before and after the customers went online. The hybrid matching method leads to an MAE for the balance of the checking accounts of 557.67, while that of the regression model is 583.86. For the number of checking accounts the hybrid matching method and regression analysis lead to an MAE of 0.07 and 0.15, respectively. Moreover, we compute a hit rate that indicates when the difference between the estimated individual treatment effect using the hybrid matching method and the observed individual effect is smaller than that for the regression model. The resulting hit rate is 55.4 percent for the balance of checking accounts and 94.3 percent for the number of checking accounts. Overall, the hybrid matching method has a higher predictive validity than the regression model and is therefore more appropriate to estimate treatment effects. Additionally, selection effects can be easily determined by the hybrid matching method which is beneficial for targeting purposes.

7 Evaluating Customer Channel Migration Activities

Since online channel use has an overall positive effect on customer profitability, we evaluate the potential impact of migrating offline customers to the online channel. Therefore, we compute the incremental change in customer profitability for each offline customer if she migrates to the online channel by:

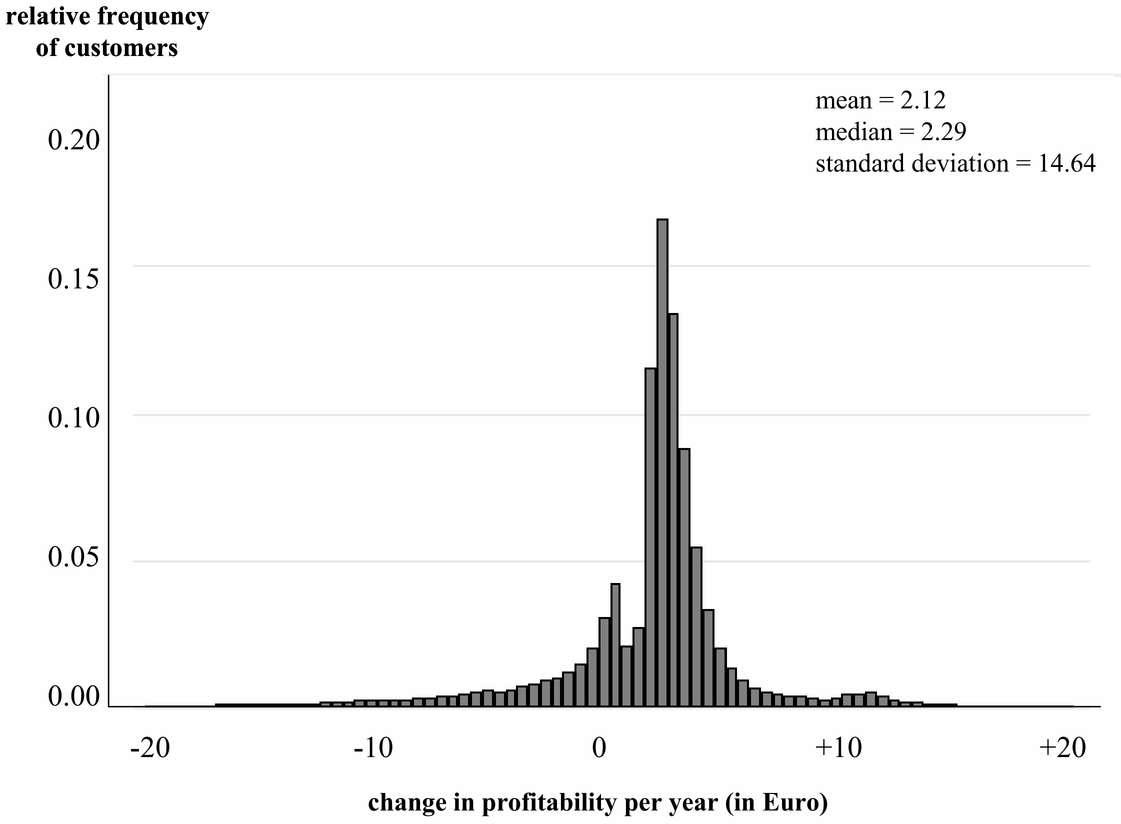
$$
\begin{aligned}
\Delta\text{profit}_j^M &= \sum_{k=1}^{K}\left[\left(Y_{k,j}^0 \middle| D=0\right)\cdot\left(1+\frac{\Delta_k^{MATTE}}{E\left[Y_{k,j}^0 \middle| D=0, P(X), x_n\right]}\right)\cdot r_k - \left(Y_{k,j}^0 \middle| D=0\right)\cdot r_k\right] \\
&= \sum_{k=1}^{K}\left[\left(Y_{k,j}^0 \middle| D=0\right)\cdot\left(\frac{\Delta_k^{MATTE}}{E\left[Y_{k,j}^0 \middle| D=0, P(X), x_n\right]}\right)\cdot r_k\right]
\end{aligned}
\qquad \forall j \in J \tag{4}
$$

where

Δprofit_j^M:	incremental change in profitability of offline customer j after migrating to the online channel,
r_k:	margin, price or cost of quantity component k.

To determine the individual incremental effect of customer migration we consider the difference between the actual customer profitability and the customer profitability after migration to the online channel. We consider a sub-sample of 95,603 offline customers. Figure 2 shows the distribution of the individual incremental effects. The mean of the distribution is 2.12 € per year. This means that customer channel migration of all current offline customers increase their profitability on average by 2.12 € per year (5.4 percent) taking their actual product usage behavior into account. Yet the high standard deviation of 14.64 € indicates that there is quite a degree of heterogeneity with respect to the individual incremental effect of customer channel migration.

Figure 2 Change in profitability for offline customers if migrated to the online channel



For 79 percent of the offline customers migration to the online channel would turn out to be profitable for this retail bank. Those customers have an average profitability of 32.73 €, whereas those offline customers for whom channel migration would have a negative effect, have an average profitability of 64.91 €. Thus, customer channel migration seems especially favorable for the less profitable customers. Migrating those customers to the online channel seems to strengthen the customer relationship and, thus, increase their profitability to a greater extent.

We estimate a binary logit model to determine whether holding a product and customer demographics have an effect on the profitability of customer channel migration activities. The dependent variable is a dummy variable representing whether a positive effect of customer channel migration from the offline to the online channel occurs or not. This variable equals 1 if the estimated incremental effect is positive and 0 otherwise. Table 7 shows the parameter estimates of this model. The younger the offline customer and the shorter the length of the customer relationship the more likely it is that channel migration will turn out to be profitable. Those customers are likely to be at the beginning of their customer lifecycle, and their relationship with the retail bank is not too strong. Furthermore, migrating offline customers without a savings account leads to a positive impact on profitability. This is due to the negative treatment effect of online-banking use on the balance of savings accounts. The number of products, holding a checking account, private loan, and brokerage account have instead a positive effect on the profitability of customer channel migration activities.

Table 7 Parameter estimates for the binary logit model

Independent variable	Parameter	p-value
Age	-0.027	0.000
Gender	0.187	0.000
Length of relationship	-0.001	0.000
Number of products	0.237	0.000
Holding of checking account	1.851	0.000
Holding of savings account	-5.768	0.000
Holding of private loan	1.034	0.000
Holding of brokerage account	1.277	0.000
N = 95,603, Pseudo R^2 = 0.45, logLikelihood = -27,042.34		

Managers are also interested in the aggregate effect of customer channel migration on profitability. The increase in customer profitability would be 5.4 percent if all offline customers were migrated to the online channel. This is due to the fact that for 21 percent of the offline customers a negative incremental effect of customer channel migration is expected. Migrating only those customers for whom the expected change in customer profitability is positive would instead result in an increase in aggregate customer profitability of 14.8 percent, not considering costs of customer channel migration. Depending on the costs of customer channel migration managers have to decide what proportion of offline customers should be migrated.

However, due to the short observation period, the estimated treatment and selection effects might not be constant over time. Hence, to evaluate the impact of customer channel migration on profitability the estimated effects have to be adapted over time.

8 Summary and Conclusions

We find that online-banking use has a positive effect on customer profitability. We show that there are substantial selection effects and we demonstrate that the treatment effect is biased when we do not account for selection effects. Accounting for selection effects leads to different managerial implications for customer channel migration activities. Decomposing customer profitability into its quantity and profitability components allows additional insights.

We find, for example, that using online banking has a strong effect on net interest received, and that transaction costs do not decrease when customers migrate to online banking.

We also demonstrate that the hybrid matching method is an appropriate approach to disentangling total differences in customer profitability into treatment and selection effects and that this method leads to reliable and stable results. Moreover, we show that the performance of the hybrid matching method is superior to standard multiple regression analysis, since the regression estimates are biased due to selection effects.

We find that customer migration to the online channel is not profitable for all offline customers: in our case relatively less profitable customers should be migrated to the online channel, whereas relatively more profitable customers should not. Customer channel migration is especially beneficial when customers do not have a savings account. One explanation might be that online customers manage their assets more efficiently and prefer products with higher flexibility. This proposition is supported by the increased number of transactions, as this is an indication of higher customer activity.

Overall, customer migration to the online channel could have a positive effect on aggregate profitability. In this study we find an increase in customer profitability of almost 15 percent. This result can also be used to evaluate the return on investments in the online channel.

To summarize we contribute to the existing literature (1) by decomposing the observed differences between online and offline customers into treatment and selection effects, (2) by determining the individual effects of customer channel migration activities on customer profitability, (3) by applying the hybrid matching method to simultaneously elicit treatment and selection effects, and by (4) contributing to the substantive knowledge base regarding managing customers in multichannel environments.

Although we focus our empirical study on retail banking and the incremental value of distribution channels, our approach can be used in a wide range of applications to disentangle treatment and selection effects due to observable variables when no strong instrumental variables exist. For instance, the evaluations of the effectiveness of loyalty programs or pricing schemes are potential candidates for applying the approach outlined in this study.

9 References

Abadie, A., Drukker, D., Leber Herr, J., & Imbens, G. W. (2001). Implementing Matching Estimators for Average Treatment Effects in Stata. *The Stata Journal*, 1(1), 1-18.

Amemiya, T. (1984). Tobit Models: A Survey. *Journal of Econometrics*, 24, 3-61.

Ansari, A., Mela, C., & Neslin, S. (2005). *Customer Channel Migration*. Working Paper, Columbia University, New York.

Black, D., & Smith, J. (2004). How Robust Is the Evidence On the Effects of College Quality? Evidence from Matching. *Journal of Econometrics*, 121, 99-124.

Cochran, W. G. (1968). The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies. *Biometrics*, 24, 205-213.

D'Agostino, R. B. (1998). Tutorial in Biostatics: Propensity Score Methods for Bias Reduction in the Comparison of a Treatment to a Non-Randomized Control Group. *Statistics in Medicine*, 17, 2265-2281.

Degeratu, A., Rangaswamy, A., & Wu, J. (2000). Consumer Choice Behaviour in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes. *International Journal of Research in Marketing*, 17, 55-78.

Dehejia, R. (2005). Program Evaluation as a Decision Problem. *Journal of Econometrics*, 125, 141-173.

Dehejia, R., & Wahba, S. (1999). Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs. *Journal of the American Statistical Association*, 94, 1053-1062.

Dehejia, R., & Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics*, 84, 151-161.

Europress Publications (2005). *Banks See Online Gain via Updated Cash Sites*. Retrieved April 7, from www.europeanbusiness.gr/SiteResources/Data/Templates/article.asp?DocID=646&par-entDocID.

Hadi, A. S. (1994). A Modification of a Method for the Detection of Outliers in Multivariate Samples. *Journal of the Royal Statistical Society (Series B)*, 56, 393-396.

Hahn, J. (1998). On the Role of the Propensity Score in Efficient Semiparametric Estimation of Average Treatment Effects. *Econometrica*, 66, 315-331.

Heckman, J. (1974). Shadow Prices, Market Wages, And Labor Supply. *Econometrica*, 58, 1121-1149.

Heckman, J. (1976). The Common Structure Of Statistical Models Of Truncation, Sample Selection, And Limited Dependent Variables And A Simple Estimator For Such Models. *Annals of Economic and Social Measurement*, 5, 475-492.

Heckman, J., Ichimura, H., Smith, A. K., & Todd, P. (1998). Characterizing Selection Bias Using Experimantal Data. *Econometrica*, 66, 1017-1098.

Hitt, L. M., & Frei, F. X. (2002). Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking. *Management Science*, 48, 732-748.

Kumar, V., & Venkatesan, R. (2005). Who Are The Multichannel Shoppers And How Do They Perform?: Correlates Of Multichannel Shopping Behavior. *Journal of Interactive Marketing*, 19, 44-62.

Lechner, M. (1998). *Training the East German Labour Force*. Heidelberg: Physica.

Lechner, M. (1999). Earnings and Employment Effects of Continuous Off-the-Job Training in East Germany After Unification. *Journal of Business & Economic Statistics*, 17, 74-90.

Lee, L.-f. (2000). Self-Selection. In B. Baltagi (Ed.), *A Companion to Theoretical Econometrics* (pp. 383-409). Malden: Blackwell.

Leenheer, J., Bijmolt, T., Van Heerde, H., & Smidts, A. (2004). *Do Loyalty Programs Enhance Behavioral Loyalty? A Market-Wide Analysis Accounting For Endogeneity*. Working Paper, Tilburg University, Tilburg.

Little, R. J. A. (1985). A Note about Models for Selectivity Bias. *Econometrica*, 53, 1469-1474.

Malone, T. W., Yates, J., & Benjamin, R. I. (1987). Electronic Markets and Electronic Hierarchies: Effect of Information Technology on Market Structure and Corporate Strategies. *Communications of the ACM*, 30, 484-497.

Myers, J., Pickersgill, A., & Van Metre, E. (2004). Steering Customers to the Right Channels. *McKinsey Quarterly*, 2004, 36-47.

Pagan, A., & Ullah, A. (1999). *Nonparametric Econometrics*. Cambridge: Cambridge University Press.

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70, 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *American Statistician*, 39, 33-38.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers*, 3, 135-146.

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, 66, 688-701.

Shankar, V., Smith, A. K., & Rangaswamy, A. (2003). Customer Satisfaction and Loyalty in Online and Offline Environments. *International Journal of Research in Marketing*, 20, 153-175.

Thomas, J. S., & Sullivan, U. Y. (2005). Managing Marketing Communications with Multichannel Customers. *Journal of Marketing*, 69, 239-251.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. Boston (Mass.): MIT Press.

Wooldridge, J. M. (2003). *Introductory Econometrics: A Modern Approach*. Mason: Thomson South West.

Zettelmeyer, F., Morton, F. S., & Silvia-Risso, J. (2003). *Cowboys or Cowards: Why are Internet Car Prices Lower?* Working Paper, National Bureau of Economic Research, Cambridge.

Zhao, Z. (2004). Using Matching To Estimate Treatment Effects: Data Requirements, Matching Metrics, And Monte Carlo Evidence. *Review of Economics and Statistics*, 86, 91-107.

Beitrag 3

Determining the Impact of Internet Channel Use on a Customer's Lifetime

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Eingereicht zum

Journal of Interactive Marketing

Juli 2006

Determining the Impact of Internet Channel Use on a Customer's Lifetime

Abstract

In light of mature markets and increasing competitive pressure, retaining the existing customer base becomes crucial for the future success of a firm. As a consequence, firms are increasingly interested in understanding the factors influencing and driving customer retention. One factor which is hypothesized to have an impact on customer retention is the growing use of the internet channel. Firms are interested in understanding whether and how the internet use induces a change in customer retention.

The aim of this paper is to quantify the impact of internet use on customer retention to derive managerial implications on how to use customer channel migration to improve overall customer retention. By pursuing this objective the necessity to account for self-selection and right-censoring is highlighted. The results of the empirical study indicate a strong positive impact of internet use on customer retention. Hence, the managerial implications are to migrate customers to the internet channel in order to increase overall retention rates.

Keywords: Customer Lifetime, Internet, Self-selection, Hazard Model

1 Introduction

In light of mature markets and increasing competitive pressure, retaining and developing the existing customer base becomes crucial for the future success of a firm. The numerous benefits of customer retention are widely recognized in the literature: (1) Most importantly, retaining customers creates a stable pool of customers for a firm's products or services (Oliver 1997). Hence, it reduces the need for seeking new and potentially risky customers (Dawes & Swailes 1999). (2) Long-term customers are willing to spend a larger share of their wallet with their preferred firm. As a consequence, they buy more products and services with the firm and generate higher revenues. (Reichheld 1996; Ganesh, Arnold, & Reynolds 2000). (3) Long-term customers are willing to pay higher prices and are less sensitive to competitive marketing activities which translates in a steady growth in revenues (Colgate, Stewart, & Kinsella 1996). (4) Loyal customers become less costly to serve due to the firm's greater knowledge of the existing customer. (5) Finally, as loyal customers tend to be satisfied with the products and services of the firm they may provide new referrals through positive word-of-mouth (Colgate, Stewart, & Kinsella 1996; Ganesh, Arnold, & Reynolds 2000).

All these benefits suggest a strong and positive link between customer retention and profitability which has already been confirmed by several empirical studies (e.g. Reichheld 1993; Rust & Zahorik 1993; Rust, Zahorik, & Keiningham 1995; Foster, Gupta, & Sjoblom 1996; Hallowell 1996; Zeithaml, Berry, & Parasuraman 1996; Mulhern 1999; Wright & Sparks 1999; Reinartz & Kumar 2000). Especially the cornerstone article on customer retention by Reichheld & Sasser (1990) which states that "reducing defections by 5% boosts profits by 25% to 85%" has emphasized this positive relationship. As a consequence, firms are increasingly interested in understanding the factors influencing and driving customer retention (Rust, Lemon, & Zeithaml 2004).

One factor which is hypothesized to have an impact on customer retention is the growing use of the internet channel among customers (Reitsma et al. 2004; Schaaf 2005). According to the U.S. Census Bureau, internet retail sales for 2000 were $25.8 billion, or 49% higher than 1999 sales of $17.3 billion (Wallace, Giese, & Johnson 2004). This rapid growth emphasizes the importance of the internet as a distribution channel and calls for a thorough investigation of the relationship between internet use and customer retention (Shankar, Smith, & Rangaswamy 2003).

The literature provides two hypotheses explaining a potential relationship between internet use and customer retention: (1) a change in customer retention induced by the use of the internet channel and (2) a self-selection of customers with above or below average loyalty levels to the internet channel (Verhoef & Donkers 2005).

Regarding the first explanation, the current literature has generated several assumptions about how the internet use might lead to a change in customer retention. Some of these assumptions suggest a negative relationship whereas others suggest a positive linkage. Shankar, Smith, & Rangaswamy (2003) for instance assume that the competition on the internet is only a few mouse clicks away. The opportunity to compare and contrast competing offerings with minimal costs causes an increase in competition based on price and hence a reduction in customer retention (Kuttner 1998; Sinha 2000). Contrasting to this, the internet is assumed as well to have a positive effect on customer retention. Compared to the offline environment, the online environment offers more opportunities for personalized marketing as well as greater flexibility and convenience to the customer (Wind & Rangaswamy 2001; Srinivasan, Anderson, & Ponnavolu 2002). Furthermore, the internet might create additional switching costs as customers learn how to use a new technology and hence improve their loyalty (Reichheld & Schefter 2000; Chen & Hitt 2002).

The second explanation for potential differences in customer retention between internet users and users of traditional channels is reasoned by the so called self-selection effect (Heckman 1990). Customers are usually offered a free choice to select a channel through which to interact with the firm (Black et al. 2002). As a consequence, customers with certain characteristics might have an intrinsic preference for a specific channel. Several studies indicate that customers using the internet are different from customers who buy from a traditional channel (Degeratu, Rangaswamy, & Wu 2000). For example, internet users are reported to be younger, better educated, and more affluent than the average population (Hitt & Frei 2002; Verhoef & Donkers 2005). But these customers are at the same time known to be less deal-prone and more loyal than other customers (Blattberg & Neslin 1990). As a consequence, the systematic differences in customer characteristics between internet users and users of traditional channels might have a direct impact on customer retention.

Even though both these theories provide an explanation for a potential difference in customer retention between internet users and users of traditional channels, the managerial implications are quite distinct: the existence of an induced change in customer retention for instance can be exploited by multi-channel managers by designing customer channel migration strategies which aim to increase overall retention of the customer base (Ansari, Mela, & Neslin 2005; Thomas & Sullivan 2005). On the other hand, customer retention rates which are different across channels due to self-selection can not be exploited by multi-channel managers. Migrating customers between the different channels would not affect retention rates (Gensler et al. 2006).

In constant search for new opportunities to increase customer retention, firms are thus primarily interested in understanding whether and how the internet use induces a change in customer retention.

The aim of this paper is to empirically quantify the impact of internet use on customer retention in order to derive managerial implications on how to use customer channel migration to improve overall customer retention. To determine an unbiased effect of internet use on customer retention the paper will account for potentially present self-selection effects.

Previous work on the impact of the internet use on customer retention has not accounted for potentially present self-selection effects and hence does not estimate an unbiased effect of internet use on customer retention. In addition, most previous work has neglected to account for the censored nature of active customer relationships when determining the average lifetime of internet users and users of traditional channels. Consequently, it can not be answered whether internet use has an impact on customer retention. Furthermore, previous research has not quantified the impact of internet use on customer retention and has therefore not derived any managerial implications for customer channel migration.

This article is structured as follows. We first discuss the literature investigating the relationship between internet use and customer retention and highlight its shortcomings. We then describe the data and methodology used for the empirical study conducted within this paper. Next, we present and discuss the results of the empirical study. We conclude by noting the managerial and research implications of the study's findings.

2 Literature Review

The literature review reveals four studies investigating the relationship between internet use and customer retention (Mols 1998; Hitt & Frei 2002; Shankar, Smith, & Rangaswamy 2003; Van den Poel & Lariviere 2004).

The first studies to investigate this issue are the articles by Mols (1998) and Hitt & Frei (2002). Both these studies use data from the financial services industry in order to determine the impact of using the internet on customer retention. Both studies reveal a positive relationship between internet use and customer retention. Mols (1998) surveys customers of several Danish financial institutions for their internet use and institutional affiliation. He then employs a correlation analysis to investigate the relationship between the binary variable internet use and the propensity to exit the financial institution. The estimated correlation coefficient suggests a positive but insignificant relationship between internet use and customer retention. Hitt & Frei (2002) use the customer database of a financial institution to observe and compare the average length of relationship of internet users versus users of traditional channels. The comparison reveals a length of relationship which is on average significantly longer for internet users compared to users of traditional channels. Hitt & Frei (2002) therefore propose a positive effect of using the internet on customer retention.

However, both studies do not account for the fact that a firm's customer base usually consists of a mix of active and completed relationships (Pfeifer & Bang 2005). Why this mix of active and completed customer relationships can cause problems in estimating the impact of internet use on customer retention becomes especially apparent for the study by Hitt & Frei (2002). Calculating the average lifetime of a customer base requires to determine the average lifetime of active and completed customer relationships. The calculation of an average lifetime for completed customer relationships is straightforward as the entire lifetime is by definition observable (Pfeifer & Bang 2005). For the active relationships on the other hand only the length of relationship to date is observable but not the eventual lifetime. In these situations, we say that the customer lifetime is subject to right censoring (Kalbfleisch & Prentice 2002). A simple averaging of the length of relationship to date of the active customers with the complete lifetimes for the completed relationships is not appropriate as it will usually underestimate the mean lifetime (Pfeifer & Bang 2005). Accounting for right-censoring is therefore a critical issue when modeling customer retention (Thomas 2001).

The ratio of active relationships compared to completed relationships is generally higher for internet users than for users of traditional channels. The results of Mols (1998) and Hitt & Frei (2002) hence underestimate the true impact of internet use on customer retention.

This weakness is addressed by Van den Poel & Lariviere (2004) by applying a hazard model to account for right-censoring. Van den Poel & Lariviere (2004) use the data of a customer database provided by a large financial institution to estimate a hazard model which relates internet use to customer retention. The results of their study indicate that the use of the internet has no significant impact on a customer's retention.

Although the study by Van den Poel & Lariviere (2004) accounts for the issue of right censoring, the study suffers from another weakness: it does not account for self-selection effects. The potential presence of self-selection effects and the lack of control for them might result in an overestimation of the effect of internet use on customer retention. In order to determine an unbiased impact of internet use on customer retention it is hence necessary to account for self-selection effects.

The literature review has identified only one study which considers and accounts for self-selection. The study by Shankar, Smith, & Rangaswamy (2003) uses the matching approach to eliminate potential self-selection effects.

The results of the study by Shankar, Smith, & Rangaswamy (2003) indicate a positive effect of the internet use on customer retention after accounting for self-selection effects. Nevertheless, the study does not consider the issue of right-censoring. Hence, the results found in this study might again be misleading.

As can be seen from Table 1 the studies investigating the relationship between internet use and customer retention can be classified according to two dimensions: whether they account for right-censoring and whether they account for self-selection. Table 1 clearly shows that none of the studies investigates the impact of internet use on customer retention and accounts at the same time for right-censoring and self-selection effects. This paper intends to close this gap in the literature in order to resolve the contradicting results in the literature and to determine the true impact of internet use on customer retention.

Table 1 Literature Review

	Account for Right-Censoring	
Account for Self-Selection	**No**	**Yes**
No	Mols 1998 Hitt & Frei 2002	Van den Poel & Lariviere 2004
Yes	Shankar, Smith, & Rangaswamy 2003	THIS PAPER

3 Sample Description

We use data from a large European retail bank to determine the impact of internet use on customer retention. Several factors underlie the decision to focus on financial services. First, internet use has a long history in the financial services industry, suggesting a reasonable degree of familiarity and adoption of the internet channel by banking customers (Hitt & Frei 2002). Second, the potential to exploit the findings of the empirical study by developing customer channel migration strategies is especially large in the financial services industry. Banks fully control the multiple channels available to the customer. Hence, they do not depend on the goodwill of intermediaries to apply customer channel migration strategies.

The data covers 10,000 customers of which 2,059 are active internet users. We define a customer as an internet user or online banking customer when she actively uses the internet channel during the observation period. The observation period covers in total 24 months from April 2002 until March 2004.

Over this 24 month period a large selection of variables has been collected for each customer. These variables can be grouped in three categories: socio-demographics, information about a customer's transaction behavior, and information about a customer's product portfolio. The socio-demographics include variables such as age and gender. The variables on a customer's transaction behavior detail the timing, the amount, and the channel used for every transaction executed in the observation period. Finally, the data set provides information about all financial products owned by the customer and their usage.

All these variables are available only for the observation period. One exception to this is the variable "length of relationship". Not all customer relationships begin within the observation period. The majority of relationships has already started before being under observation. Hence, these customers were already at risk of leaving the bank before being observed. Had a customer churned earlier, we never would have encountered this customer in the data set. This problem is called left truncation and has to be accounted for when estimating the average lifetime of customers (Cleves, Gould, & Gutierrez 2004).

The second problem which arises in the data set is the issue of self-selection. In our sample internet users are younger and have a higher likelihood to be female. Furthermore, internet users have a higher likelihood to be phone banking customers, to own more products, and to do more transactions (see Table 2). As these variables may directly impact a customer's lifetime (Blattberg & Neslin 1990), it is necessary to account for the problem of self-selection in this data set (Cochran & Rubin 1973).

The third problem which arises in the data is the issue of right-censoring. Out of the total 10,000 customers only 1,237 are being observed to churn within the observation period. We define a churned customer as someone who closed all her accounts. The remaining 8,763 customer relationships are not completed yet and are therefore right-censored.

Table 2 Selected Customer Characteristics for Internet Users and Users of Traditional Channels

	Internet Users (2059 observations)	Non-Internet Users (7941 observations)	Significance of difference
Age (in years)	22.6	29.4	0.0000
Gender (% being male)	49.5 %	51.8 %	0.0667
Penetration of Phone Banking	7.1 %	0.3 %	0.0000
# of Products per Customer	1.3	1.4	0.0000
Penetration of Security Accounts	2.2 %	3.1 %	0.0378
# of Transactions per Customer	6.6	4.0	0.0000

4 Methodology

As has been shown accounting for self-selection and right-censoring is important as ignoring them might lead to biased results. The following paragraphs will exhibit a two stage process employing two distinct statistical methods to first account for self-selection and then for right-censoring. We describe the basic idea and the application of the two statistical methods.

4.1 Methodology to Account for Self-Selection Effects

The problem of self-selection is generally defined as a sampling problem. Customers are selected in the group of internet users by means other than random sampling (Dehejia & Wahba 1999). One approach to account for this distorted sampling and hence for self-selection effects is the matching approach introduced by Rubin (1979). The matching approach intends to rebuild random sampling in a non-experimental context (Rosenbaum & Rubin 1983; Rosenbaum & Rubin 1985). Its basic idea is to find in a large group of non-internet users those individuals who are similar to the internet users with respect to specific covariates (Heckman, Ichimura, & Todd 1998). Covariates are variables that simultaneously have an impact on a customer's lifetime and on a customer's decision to use the internet channel (Sianesi 2004; Smith & Todd 2005). Ideally, the matched customers are identical to each other except for their use of the internet. That being done, differences in customer lifetime between the group of internet users and this well selected group of users of traditional channels can be attributed to internet use.

The application of the matching method requires three steps: First it is necessary to determine the covariates which simultaneously impact a customer's lifetime and channel use (Rosenbaum 2002). The selection of the relevant covariates should be based on economic theory and previous research (Sianesi 2004; Smith & Todd 2005). After the relevant covariates have been identified, the similarity between individuals with respect to these covariates has to be determined. A common approach to determine this similarity is the so called covariate matching (Zhao 2004). Covariate matching uses a distance measure such as the Mahalanobis distance to calculate the similarity between two individuals in terms of covariate values (Imbens 2004). The final step is to match customers based on their similarity. A straightforward approach is to match each internet user to one user of traditional channels (one-to-one-matching) (Cochran & Rubin 1973). The search for matching individuals can be conducted either with or without replacement. "With replacement" signifies that users of traditional channels can be used in several occasions as matching partners. We use matching with replacement as it enhances the fit of the matched pairs and therefore eliminates self-selection bias more efficiently (Smith & Todd 2005). After having accounted for the self-selection effects by means of the matching method, it is now possible to account for the problem of right-censoring based on the matched sample.

4.2 Methodology to Account for Right-Censoring

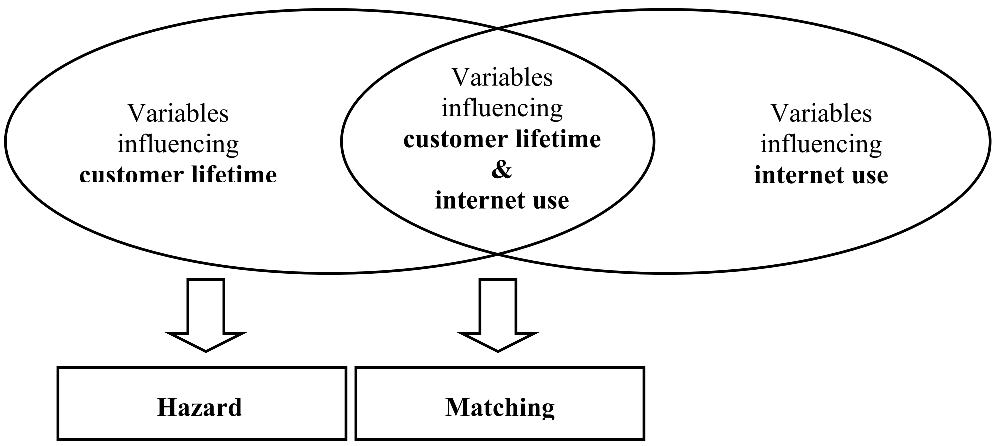
The problem of right-censoring arises when customers are still active at the end of an observation period. Thus, it is not observable whether a customer will churn one day or twenty years after the observation period ends (Pfeifer & Bang 2005). One statistical method to account for right-censored observations are hazard models (Cox & Oakes 1996). The aim of hazard models is to relate the occurrence of events – for instance the churn of a customer – to a function of covariates (Hosmer & Lemeshow 1999; Klein & Moeschberger 2003). Covariates used in hazard models are defined as variables which are assumed to have an impact on a customer's lifetime (Kalbfleisch & Prentice 2002). This estimated hazard model can be used to predict a customer's lifetime and thus account for right-censoring (Cox & Oakes 1996).

The application of hazard models requires three steps: the first step is to identify covariates functioning as predictors of a customer's lifetime based on economic theory and previous research. The second step in modeling survival time requires to chose the parameterization of the survival function. Three types of hazard models can be distinguished: non-parametric, semi-parametric, and parametric models (Klein & Moeschberger 2003). We opt for a parametric model as it is superior when intending to predict survival time (Cleves, Gould, & Gutierrez 2004, p. 232) and more efficient in exploiting the available data compared to non-parametric and semi-parametric models (Cleves, Gould, & Gutierrez 2004, p. 200). The third step in applying parametric hazard models is to choose a functional form for the baseline hazard. The choice of the distribution determines whether the hazard rate of the population under observation is increasing, decreasing, or constant over time. One particular distribution which is flexible enough to accommodate increasing, decreasing, and constant hazard rates is the Weibull distribution. We therefore opt for the Weibull distribution as it provides the necessary flexibility of the hazard model.

5 Empirical Design

As indicated in the methodology section to account for self-selection and right-censoring it is necessary to apply a two stage process using the matching method and a hazard model. The application of the matching method requires to identify covariates simultaneously influencing customer retention and internet use (see Figure 1). Using a hazard model to estimate a customer's lifetime requires to identify all relevant covariates having an impact on customer lifetime. This includes the variable of interest – in our case the use of the internet channel – and additional variables to control for their effect on customer lifetime. In the following, we use economic theory and previous research to first identify the covariates simultaneously having an impact on customer lifetime and internet use and afterwards additional covariates having only an impact on customer lifetime.

Figure 1 Relationship between Covariates for Matching and Hazard Models



5.1 Variables Influencing Simultaneously Customer Lifetime and Internet Use

Several studies indicate socio-demographic variables as well as variables describing a customer' transaction and product usage behavior to impact customer lifetime and internet use simultaneously. Among the socio-demographic variables this includes age and gender.

Age. Mittal & Kamakura (2001) argue that older people have more stable preferences and thus show lower switching tendencies. Hence, the likelihood to churn should be decreasing with age.

At the same time, Inman, Shankar, & Ferraro (2004) find a significant impact of age on a customer's channel choice. Younger customers seem to have a preference for the internet channel (Shankar, Smith, & Rangaswamy 2003). Thus, a simultaneous impact of age on customer lifetime and internet use can be supported based on the reviewed literature.

Gender. Dekimpe & Degraeve (1997) and Mittal & Kamakura (2001) study the impact of gender on customer retention. Dekimpe & Degraeve (1997) show that women have a higher churn probability whereas contrasting results are found by Mittal & Kamakura (2001). Despite the contradicting findings, an impact of gender on customer retention can be hypothesized.

Simultaneously, studies identify an impact of gender on a customer's channel choice (Verhoef & Donkers 2005). Devlin & Yeung 2003 for instance exhibit a significant impact of being male on internet use. Hence, it can be confirmed that gender has an impact on customer lifetime and on internet use.

Two variables describing a customer's transaction behavior simultaneously impact customer lifetime and internet channel use: The number of transactions and phone banking use (Montoya-Weiss, Voss, & Grewal 2003; Boehm & Gensler 2005).

Number of transactions. An increase in the number of transactions is assumed to be negatively correlated with a customer's propensity to churn (Schmittlein, Morrison, & Colombo 1987). On the one hand, it can be argued that an increasing number of transactions results in a growing familiarity with the service offering of a firm and hence in a strengthening of the customer-firm relationship (Bendapudi & Berry 1997). On the other hand, an increasing number of transactions might be the result of a customer being satisfied with a firm's service offering (Morgan & Hunt 1994).

The argumentation supporting an impact of the number of transactions on internet use is based on the lower transaction costs incurred by customers on the internet (Durkin et al.

2003). Transactions conducted through the internet do not incur the opportunity costs which stem from traveling to the bank or waiting in the queue (Campbell 2003). Customers conducting many transactions can over-proportionately benefit from these cost savings. Thus, it can be assumed that the likelihood of using the internet increases with the number of transactions being conducted by the customer. As a consequence, a joint impact of the number of transactions on customer lifetime and on internet use can be confirmed.

Phone banking. Phone banking provides customers with the possibility to conduct transactions independently from any bank opening hours (Black et al. 2002). This contributes to the convenience perceived by the customer (Durkin et al. 2003). The increased convenience again translates into a positive effect on customer retention (Stone, Hobbs, & Khaleeli 2002).

The phone and the internet channel are both remote channels of interaction and hence do not offer the possibility of a face-to-face interaction (Morrison & Roberts 1998). Phone banking customers have already learned to deal with their bank without face-to-face interaction. Due to the similarity of channel characteristics the likelihood of using the internet should be higher for phone banking users (Montoya-Weiss, Voss, & Grewal 2003). Phone banking use is therefore likely to have an impact on customer lifetime and internet use.

Finally, we identify the variables describing a customer's product usage behavior which simultaneously impact customer lifetime and internet use: the number of products and the ownership of a securities account.

Number of products. Previous research exhibits an impact of the total number of products used by a customer on customer retention. Huber, Lane, & Pofcher (1998) for instance reveal in their study that the more products a customer owns from one specific firm, the longer she is likely to remain a customer.

At the same time, it is argued that the likelihood of internet use increases with the number of products owned. The internet channel enables customers to manage their products more efficiently (Hitt & Frei 2002). Customers who use multiple products and hence bear a complex management task are more inclined to adopt the internet channel. As a consequence, these customers have a larger likelihood to remain with the firm and to use the internet.

Ownership of a securities account. Some researchers investigate not only the impact of the number of products but as well the product-specific ownership on customer retention (Levesque & McDouglas 1996; Athanassopoulos 2000). Especially the ownership of a securities account is hypothesized to impact customer lifetime.

Similarly, the likelihood of adapting the internet channel increases for customers owning a securities account (Hitt & Frei 2002). Especially, the increased convenience of managing a securities account online attracts many customers to the internet channel (Greywitt & Tews 2001). Hence, the ownership of a securities account simultaneously impacts customer lifetime and internet use.

5.2 Additional Variables Influencing Customer Lifetime

After having identified the variables influencing simultaneously customer lifetime and internet channel use we now highlight additional variables which are hypothesized to have only an impact on customer lifetime and hence to be included in the hazard model. Although the focus of this study is to determine the impact of internet use on customer retention, we also include additional variables in the hazard model in order to control for their effect. Not controlling for these additional variables would results in biased estimates for the impact of internet use on customer retention.

The length of relationship and the interpurchase time are two additional variables describing a customer's transaction behavior which are hypothesized to influence customer lifetime.

Length of relationship. The literature indicates an impact of a customer's tenure with the firm on her churn behavior (Reichheld 1996). One explanation might be that long-term customers develop a habitual purchase behavior (Waller 1988). They have become accustomed to purchase the products and services of a specific firm. As a consequence, they waive their opportunity to search for competitive offerings. In addition, the trust which is building up over a long-term relationship positively influences the repurchase intention (Ganesan 1994).

Interpurchase time. An increasing purchase frequency and hence a decrease in the interpurchase time might lead to a reduction in customer churn (Bhattacharya 1998; Watson, Akselsen, & Pitt 1998). Vilcassim & Jain (1991) for instance found that with the passage of time between two purchases the likelihood of churn increases.

Variables describing a customer's product usage behavior which are hypothesized to be related to customer retention include ownership of a joint account, volatility of deposits, and the customer profitability.

Ownership of a joint account. Research shows that owners of a joint account have a lower likelihood to churn than the average customer base (Eickbusch 2002). One explanation might be that customers will not install any additional user for their account unless they are satisfied with the services offered by the bank (Hüppelshäuser 2005). Another explanation is based on the assumption that joint accounts increase switching costs (Chen & Hitt 2002).

Volatility of deposits. The volatility of deposits is defined as the cumulative percentage change across all deposits of a customer compared to the previous period. A large negative volatility indicates a sharp drop in a customer's assets deposited with the bank. One explanation of a sharp drop in a customer's assets might be that a customer is planning to close all accounts and is beginning to transfer all assets to a competitor. Thus volatility of deposits functions as a predictor of customer churn (Bienenstock, Bonomo, & Hunter 2004).

Table 3 Overview of Variables for Matching Method and Hazard Model

	Supporting reference for impact on	
	Internet Use (Stage 1 – Matching Method)	**Customer Lifetime** (Stage 2 – Hazard Model)
Socio-Demographics		
Age	Inman, Shankar, & Ferraro 2004 Lee 2002	Athanassopoulos 2000 Colgate & Danaher 2000
Gender	Lee 2002 Verhoef & Donkers 2005	Dekimpe & Degraeve 1997 Mittal & Kamakura 2001
Transaction Behavior		
# of Transactions	Boehm & Gensler 2005	Schmittlein, Morrison, & Colombo 1987
Phone Banking	Montoya-Weiss, Voss, & Grewal 2003 Eastlick & Liu 1997	Van den Poel & Lariviere 2004
Length of relationship	-	Reichheld 1996 Ganesan 1994
Interpurchase time	-	Bhattacharya 1998 Watson, Akselsen, & Pitt 1998
Customer Product Portfolio		
# of Products	Raijas & Tuunainen 2001	Huber, Lane, & Pofcher 1998 Van den Poel & Lariviere 2004
Ownership of securities account	Hitt & Frei 2002 Greywitt & Tews 2001	Athanassopoulos 2000 Levesque & McDouglas 1996
Ownership of joint account	-	Ganesan 1994 Jones, Mothersbaugh, & Beatty 2002
Volatility	-	Bienenstock, Bonomo, & Hunter 2004
Customer profit	-	Levin & Zahavi 1996 Baesens et al. 2002
Main Effect		
Internet use	-	Mols 1998 Chen & Hitt 2002

Customer profitability. The impact of customer profitability on customer retention is indirectly derived from a study that suggests a positive relationship between monetary value and repurchase tendencies (Baesens et al. 2002). The general convention is that the more money a customer has spent with a company, the higher the likelihood of purchasing again (Levin & Zahavi 1996).

Table 3 summarizes the variables having a simultaneous impact on customer lifetime and internet use and hence being used to account for self-selection as well as the variables having an impact on internet use and hence being used to account for right-censoring.

6 Findings

6.1 Quality of Matching Method to Account for Self-Selection Effects

The matching method is intended to eliminate systematic differences between the group of internet users and the users of traditional channels and hence to account for self-selection effects. The quality of the matching procedure can therefore be evaluated on whether systematic differences are still present after matching (Rosenbaum & Rubin 1985; Smith & Todd 2005). Table 4 presents a comparison between internet users and the group of matched users of traditional channels. The comparison reveals a similar distribution for the relevant characteristics across both customer groups. Most differences in customer characteristics between both groups are insignificant after matching. Another suitable indicator to assess the quality of the matching procedure is the standardized bias (SB) suggested by Rosenbaum & Rubin (1985). The standardized bias for all relevant characteristics is reduced significantly by the proposed matching procedure. Hence, the percentage reduction in bias suggests an acceptable quality level of the matching procedure. It can therefore be assumed that the self-selection bias present in the data is eliminated by the proposed matching procedure.

Table 4 Selected Variables for Internet Users and Matched Users of Traditional Channels

	Internet Users (2059 observations)	Matched Non-Internet Users (1336 observations)	Significance of difference
Age (in years)	22.6	22.5	0.1728
Gender (% being male)	49.5 %	51.4 %	0.2714
Penetration of Phone Banking	7.1 %	1.3 %	0.0000
# of Products per Customer	1.3	1.3	0.1376
Penetration of Security Accounts	2.2 %	2.3 %	0.8317
# of Transactions per Customer	6.6	6.1	0.0039

6.2 Quality of Hazard Model to Account for Right-Censoring

Hazard models account for right-censoring by predicting the expected lifetime for active customer relationships. The capability of the hazard model to account for right-censoring can therefore be evaluated based on the model's capability to accurately predict customer lifetimes. In order to evaluate the predictive validity of the model we split the available data in an estimation and validation sample. The estimation sample covers the first 20 months and the validation sample the last four months of the 24 months observation period. We then use a predictive validity measure to evaluate the accuracy of the forecasts. A dimensionless predictive validity measure which relates the predicted to observed customer lifetimes is the Corrected Mean Absolute Percentage Error (MAPE) (Armstrong 1985). Studies have shown MAPE to be a reliable predictive validity measure (Armstrong & Fildes 1995). The MAPE for the estimated hazard model is 13.2 percent which represents a good forecast accuracy (Armstrong 1985). Hence, a good quality of the estimated hazard model to account for right-censoring can be confirmed.

6.3 Results of Hazard Model

The results of the estimated hazard model are depicted in Table 5. In general, some interesting results emerge from our analysis.

Table 5 Estimation Results of Hazard Model

	Hazard Ratio	**Z**	**P > z**
Age	0.969	-1.67	0.094
Gender	1.190	1.76	0.079
Length of relationship	0.965	-4.62	0.000
# of transactions	1.012	1.08	0.278
Interpurchase time	0.996	-0.58	0.563
Phone banking	1.676	0.89	0.375
# of products	0.191	-10.34	0.000
Joint account	0.831	-0.80	0.427
Securities account	0.164	-2.41	0.016
Volatility	1.000	-0.83	0.407
Profitability	1.031	4.23	0.000
P	1.727	11.76	0.000
Internet use	0.126	-5.66	0.000

In terms of socio-demographic variables we find that older customers are less likely to end the relationship with the bank. Every additional year of age decreases the likelihood of churn by 3.1 percent. This finding is in line with the results of the empirical study by Van den Poel & Lariviere (2004) and supports our assumed relationship. Similarly, we can confirm that men experience shorter lifetimes compared to women. Possible explanations can be found in the fact that women are more tolerant than men (Mittal & Kamakura 2001) or that men may exhibit higher involvement towards financial products (Van den Poel & Lariviere 2004).

Contrasting to the socio-demographic variables, the variables describing a customer's transaction behavior seem to have only a limited impact on a customer's lifetime. Except for length of relationship all transaction behavior variables show no significant impact on customer lifetime including the number of transactions, the interpurchase time, and the phone banking use.

The length of relationship, shows a positive impact on a customer's lifetime. Tenured customers, as expected, tend to have longer lifetimes compared to customers who are with the firm only for a short period of time.

Regarding the number of transactions it was argued that they reflect a customer's financial activity with the bank. Active customers are assumed to have a strong customer-firm relationship. But, the estimation results show that the number of transactions neither has a positive nor a negative impact on customer lifetime. One explanation might be that customers leaving a bank as well have to display an increased level of activity. The insignificant impact of the interpurchase time can be reasoned by the long interpurchase times in the financial services industry. Customers in the financial services industry exhibit an average interpurchase time of more than four years (Kamakura et al. 2003). The limited observation period combined with such a long interpurchase time could provide an explanation for the insignificant effect. The insignificant effect of phone banking use on customer retention might be due to the fact that phone banking has become a commodity service. The majority of banks offers this service and can not use it as a factor of differentiation.

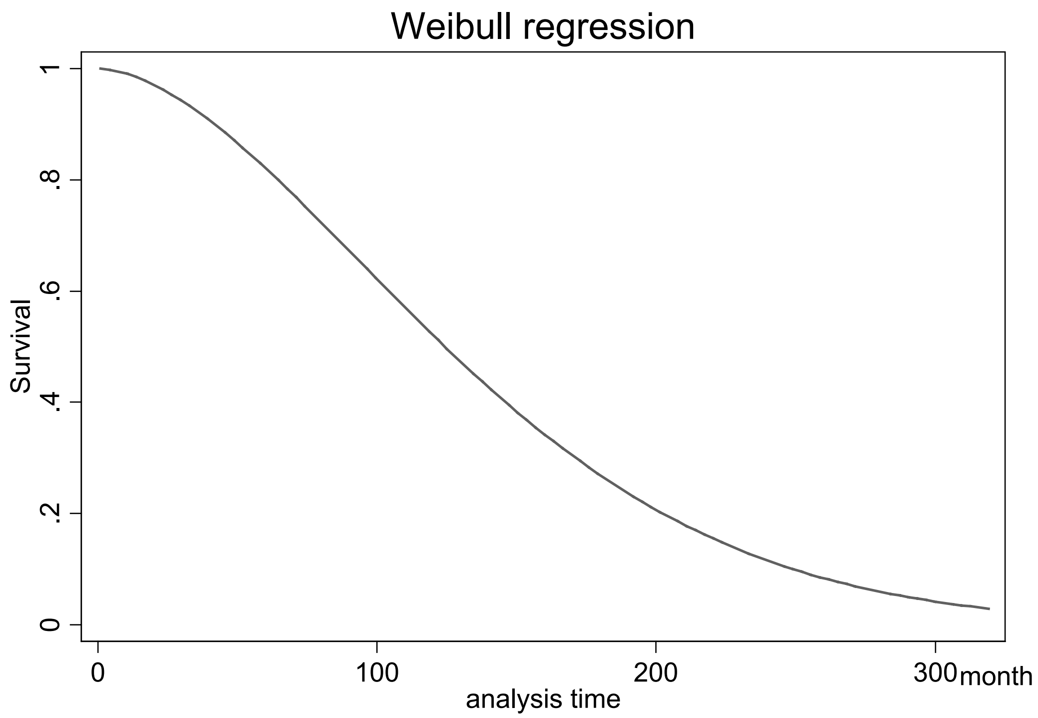
Our results reveal a significant impact for the majority of variables describing a customer's product usage behavior. The number of products used by the customer dramatically reduces the likelihood to churn. Each additional product reduces the churn probability by more than 80 percent. This relationship confirms the relevance of cross-selling activities in the financial services industry (McKelvey 2004). Cross-selling seems not only to increase revenues generated with the customer but as well to prolong customer relationships (Van den Poel & Lariviere 2004). Especially securities accounts seem to be an adequate product for cross-selling with the aim to increase a customer's lifetime. Our results suggest that the ownership of a securities account improves the likelihood of retaining a customer by 83.4 percent. Contrasting to this the ownership of a joint account, which was hypothesized to positively impact a customer's lifetime, does not exhibit a significant effect. Similarly, the volatility of deposits has no significant effect on customer churn. An explanation might be that customers undergo a slow churn process rather than quickly transferring all assets in anticipation of leaving the bank. This issue has already been discussed in the literature under the topic of partial defection (Buckinx & Van den Poel 2005).

The last variable being evaluated for an impact on a customer's lifetime is customer profitability. Contrasting to the hypothesized effect, customer profitability displays a hazard ratio above one and hence a negative effect on a customer's lifetime. The results indicate that an increase in profitability reduces the probability of retaining the customer by 3.1 percent. An explanation of this relationship might be that this specific bank tends to increase customer profitability by increasing prices. Price increases on the other hand might drive customers to the competition.

Table 5 not only contains the estimated hazard ratios of the hazard model, but as well its ancillary shape parameter. The shape parameter which is estimated by the data indicates whether the population experiences constant, increasing, or decreasing hazard rates as time passes. The estimated shape parameter indicates increasing hazard rates for the population. In other words, the likelihood of an instantaneous customer churn increases as time passes. This significant estimation result supports as well our choice of the Weibull distribution as a parameterization of the baseline hazard.

Figure 2 represents the estimate of the survival curve for all customers included in this study. The survival curve is predicted based on all estimated parameters – including significant and insignificant parameters – to improve prediction (Hansen 1987). The plot shows a decreasing shape reflecting the fact that the longer an individual has been a customer the smaller her probability of survival. We observe that the probability of churn is accelerating after an initial period of four years and is slowing down again after being with the bank for ten years.

Figure 2 Survival Function for Full Sample



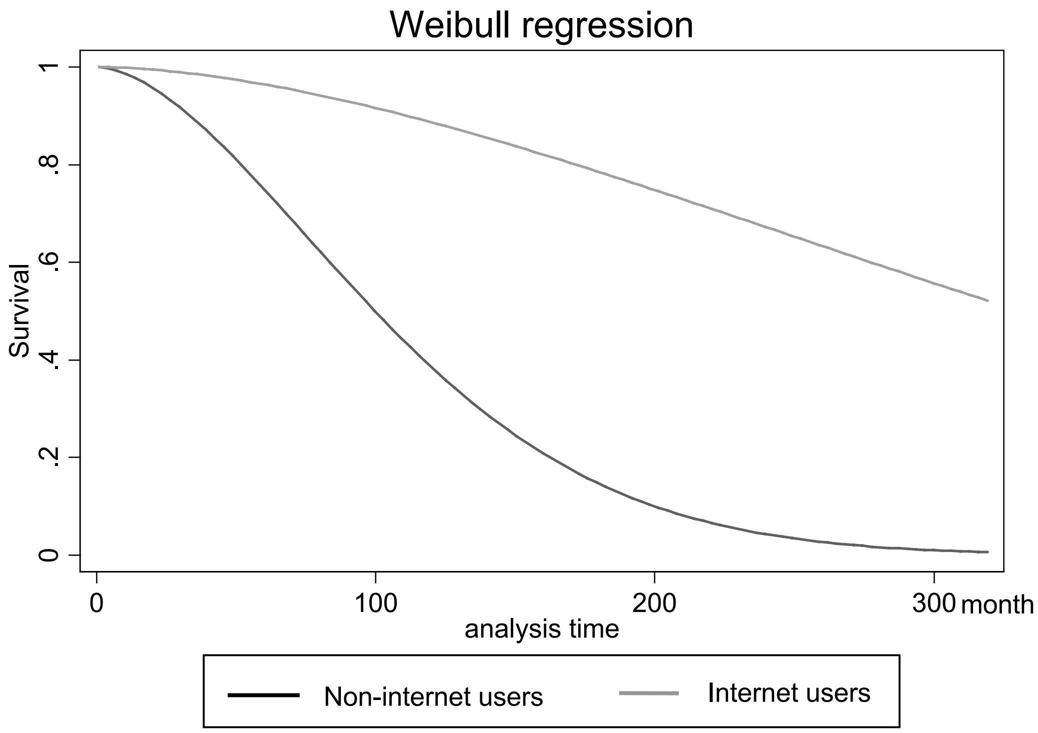
The estimated mean survival time as seen in Figure 2 is approximately 300 months and represents an average customer lifetime of twenty-five years. This estimate of the average customer lifetime appears plausible and is similar to previous findings in the literature (Van den Poel & Lariviere 2004). This result supports the predictive validity of the estimated hazard model.

6.4 Impact of Internet Use on a Customer's Lifetime

The aim of the paper is to determine the impact of internet use on a customer's lifetime. As can already be seen from the estimated hazard ratios in Table 5 internet use has a positive effect on a customer's lifetime. Using the internet reduces the likelihood of churn by 87.6 percent. This dramatic decrease becomes apparent when comparing the survival function of internet users with users of traditional channels. This comparison is depicted in Figure 3.

The survival function of the internet users lies considerably above the function of the users of traditional channels indicating a higher probability of survival. For the internet users the probability of remaining a customer after five years is 97 percent while the corresponding probability of non-internet users is 75 percent. This comparison already shows the significant impact of using the internet on customer retention. This empirical result proves any hypothesis about a negative effect of internet use on customer retention wrong. At least in an industry such as financial services where trust is an important factor when selecting the provider of choice negative effects of introducing the internet are clearly out-weighted (Lee & Marlowe 2003). Instead customers using the internet experience higher switching costs or an improved convenience which reduces the likelihood of churn.

Figure 3 Comparison of Survival Function of Internet Users and Users of Traditional Channels



The estimation results indicate that multi-channel managers interested in increasing the retention of their customer base can use customer channel migration to reduce the churn rate among their customers. More precisely, they should intend to migrate customers to the internet channel or motivate newly acquired customers to use the internet channel. Our results even show that migrating customers to the internet channel is more effective than using cross-selling activities in increasing customer retention. As a consequence, multi-channel managers should be interested in focusing a larger share of their marketing efforts on customer channel migration rather than on cross-selling activities.

The results of this empirical study provide a clear added value to multi-channel managers compared to the results of previous studies investigating the relationship between internet use and customer retention. Rather than determining only the presence of an effect of internet use on customer retention, the estimates of this empirical study quantify exactly the impact of internet use on a customer's probability to remain with the firm. As a consequence, multi-channel managers can calculate by how many years a customer's lifetime is extended when being migrated to the internet channel. This offers the opportunity to evaluate whether the return on customer channel migration will be positive or negative.

7 Conclusion

Customer retention generates numerous benefits and hence is a critical aim of many firms. A small shift in customer retention can already make a large difference for the profitability of the firm. As a consequence, firms are increasingly interested in understanding the factors driving customer retention. One factor which is hypothesized to have an impact on customer retention is the growing use of the internet channel. Firms are interested in understanding whether and how the internet use induces a change in customer retention.

The aim of this paper was to empirically quantify the impact of internet use on customer retention in order to derive managerial implications on how to use customer channel migration to improve overall customer retention.

A literature review identified four studies investigating the relationship between internet use and customer retention. Nevertheless, all four studies suffer from methodological weaknesses. They either do not account for the issue of self-selection or the issue of right-censoring. However, not accounting for self-selection will tend to overestimate whereas not accounting for right-censoring will tend to underestimate the true impact of internet use on customer retention.

We therefore proposed a two stage process using two statistical methods to account for the issue of self-selection and the issue of right-censoring. In the first stage we employed the matching method to eliminate potentially present self-selection. In the second stage we estimated a hazard model on the matched sample in order to estimate a customer's lifetime and hence to account for right-censoring.

The results of the empirical study indicate a strong positive impact of internet use on customer retention. The use of the internet channel has been shown to reduce the risk of churn by nearly 88 percent. Customers using the internet channel exhibit therefore a significantly longer average lifetime.

The results of the empirical study identify customer channel migration as an effective measure to increase the retention of a firm's customer base. Multi-channel managers interested in reaping the benefits of increased customer retentions should therefore intend to raise the use of the internet channel among customers. This will allow to significantly prolong the average customer lifetime with the firm. The estimates of the hazard model even suggest that migrating customers to the internet channel has a larger effect on customer retention than cross-selling activities aiming to sell one additional product. This finding emphasizes the relevance of customer channel migration for the future success of a firm.

In summary, we contribute to the literature by (1) empirically determining the impact of internet use on customer retention, (2) by deriving managerial implications for customer channel migration strategies, (3) by accounting for self-selection and right-censoring in the data, and finally (4) by applying a combination of the matching method and hazard models to a marketing problem.

8 References

Ansari, A., Mela, C., & Neslin, S. (2005). *Customer Channel Migration*. Working Paper, Columbia University, New York.

Armstrong, J. S. (1985). *Long-Range Forecasting: From Crystal Ball to Computer*. New York: John Wiley & Sons.

Armstrong, J. S., & Fildes, R. (1995). Correspondence on the Selections of Error Measures for Comparisons Among Measures. *Journal of Forecasting*, 14, 67-71.

Athanassopoulos, A. D. (2000). Customer Satisfaction Cues to Support Market Segmentation and Explain Switching Behavior. *Journal of Business Research*, 47, 191-207.

Baesens, B., Viaene, S., Van den Poel, D., Vanthienen, J., & Dedene, G. (2002). Bayesian Neural Network Learning for Repeat Purchase Modelling in Direct Marketing. *European Journal of Operational Research*, 138, 191-211.

Bendapudi, N., & Berry, L. L. (1997). Customers' Motivation for Maintaining Relationships with Service Providers. *Journal of Retailing*, 73, 15-37.

Bhattacharya, C. B. (1998). When Customers Are Members: Customer Retention in Paid Membership Contexts. *Journal of the Academy of Marketing Science*, 26, 31-44.

Bienenstock, R., Bonomo, P., & Hunter, R. (2004). Keeping Mobile Customers. *McKinsey Quarterly*, 9.

Black, N. J., Lockett, A., Ennew, C., Winklhofer, H., & McKechnie, S. (2002). Modelling Consumer Choice Of Distribution Channels: An Illustration from Financial Services. *International Journal of Bank Marketing*, 20, 161-173.

Blattberg, R. C., & Neslin, S. A. (1990). *Sales Promotion: Concepts, Methods and Strategies*. Englewood Cliffs: Prentice Hall.

Boehm, M., & Gensler, S. (2005). *Evaluating the Impact of the Online Sales Channel on Customer Profitability*. Paper presented at the Hawaii International Conference on System Sciences, Hawaii, USA.

Buckinx, W., & Van den Poel, D. (2005). Customer Base Analysis: Partial Defection of Behaviorally-Loyal Clients in a Non-Contractual FMCG Retail Setting. *European Journal of Operational Research*, 164, 252-268.

Campbell, D. (2003). *The Cost Structure and Customer Profitability Implications of Electronic Distribution Channels: Evidence from Online Banking*. Working Paper, Harvard Business School, Cambridge.

Chen, P.-Y., & Hitt, L. M. (2002). Measuring Switching Costs And The Determinants Of Customer Retention In Internet-enabled Businesses: A Study Of The Online Brokerage Industry. *Information Systems Research*, 13, 255-276.

Cleves, M. A., Gould, W. W., & Gutierrez, R. G. (2004). *An Introduction to Survival Analysis Using Stata*. College Station: Stata Press.

Cochran, W. G., & Rubin, D. B. (1973). Controlling Bias in Observational Studies. *Sankhya*, 417-447.

Colgate, M. R., & Danaher, P. J. (2000). Implementing a Customer Relationship Strategy: The Asymmetric Impact of Poor versus Excellent Execution. *Journal of the Academy of Marketing Science*, 28, 375–387.

Colgate, M. R., Stewart, K., & Kinsella, R. (1996). Customer Defection: A Study of the Student Market in Irland. *International Journal of Bank Marketing*, 14, 23-29.

Cox, D. R., & Oakes, D. (1996). *Analysis of Survival Data*. London: Chapman & Hall.

Dawes, J., & Swailes, S. (1999). Retention sans Frontieres: Issues for Financial Services Retailing. *International Journal of Bank Marketing*, 17, 36-43.

Degeratu, A., Rangaswamy, A., & Wu, J. (2000). Consumer Choice Behaviour in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes. *International Journal of Research in Marketing*, 17, 55-78.

Dehejia, R., & Wahba, S. (1999). Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs. *Journal of the American Statistical Association*, 94, 1053-1062.

Dekimpe, M. G., & Degraeve, Z. (1997). The Attrition of Volunteers. *European Journal of Operational Research*, 98, 37–51.

Devlin, J. F., & Yeung, F. T. (2003). Insights into Customer Motivations for Switching to Internet Banking. *International Review of Retail, Distribution and Consumer Research*, 13, 375-392.

Durkin, M., McCartan-Quinn, D., O'Donnell, A., & Howcroft, B. (2003). Retail Bank Customer Preference: Personal and Remote Interactions. *International Journal of Retail & Distribution Management*, 31, 177-189.

Eastlick, M. A., & Liu, M. (1997). The Influence of Store Attitudes and other Non-Store Shopping Patterns on Patronage of Teleshopping. *Journal of Direct Marketing*, 11, 14-25.

Eickbusch, J. (2002). *Kundenabwanderungen in Kreditinstituten [Customer Defection at Financial Institutions]*. Frankfurt: Knapp.

Foster, G., Gupta, M. R., & Sjoblom, L. M. (1996). Customer Profitability Analysis: Challenges and New Directions. *Journal of Cost Management*, 10, 5-17.

Ganesan, S. (1994). Determinants of Long-Term Orientation in Buyer-Seller Relationships. *Journal of Marketing*, 58, 1-19.

Ganesh, J., Arnold, M. J., & Reynolds, K. E. (2000). Understanding the Customer Base of Service Providers: An Examination of the Differences between Switchers and Stayers. *Journal of Marketing*, 64, 65-87.

Gensler, S., Boehm, M., Leeflang, P. S. H., & Skiera, B. (2006). *Effect of Channel Use on Customer Profitability*. Working Paper, Johann Wolfgang Goethe-University, Frankfurt.

Greywitt, M., & Tews, J. (2001). *2001 Future Online Market Penetration Study*. White Paper, Agoura Hills: J. D. Power and Associates.

Hallowell, R. (1996). The Relationship of Customer Satisfaction, Customer Loyalty, and Profitability. An Empirical Study. *International Journal of Service Industry Management*, 7, 27-42.

Hansen, G. (1987). Forecasting Error and Multicollinearity. In, *Jahrbuch für Nationalökonomie und Statistik* (pp. 517-531). Stuttgart: G. Fischer Verlag.

Heckman, J. (1990). Varieties of Selection Bias. *The American Economic Review*, 80, 313-318.

Heckman, J., Ichimura, H., & Todd, P. E. (1998). Matching as an Econometric Evaluation Estimator. *Review of Economic Studies*, 65, 261-294.

Hitt, L. M., & Frei, F. X. (2002). Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking. *Management Science*, 48, 732-748.

Hosmer, D. W., & Lemeshow, S. (1999). *Applied Survival Analysis - Regression Modeling of Time To Event Data*. New York: John Wiley & Sons.

Huber, C. P., Lane, K. R., & Pofcher, S. (1998). Format Renewal in Banks - It's Not That Easy. *McKinsey Quarterly*, 148-154.

Hüppelshäuser, M. (2005). *Ertragsorientierte Kundenbindung im Rahmen des Kundenmanagements [Value-Oriented Customer Retention as a Part of Customer Management]*. Vallendar: Wiss. Hochsch. für Unternehmensführung.

Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *Review of Economics and Statistics*, 86, 4-29.

Inman, J. J., Shankar, V., & Ferraro, R. (2004). The Roles of Channel-Category Associations and Geodemographics in Channel Patronage. *Journal of Marketing*, 68, 51-71.

Jones, M. A., Mothersbaugh, D. L., & Beatty, S. E. (2002). Why Customers Stay: Measuring the Underlying Dimensions of Service Switching Costs and Managing Their Differential Strategic Outcomes. *Journal of Business Research*, 55, 441-450.

Kalbfleisch, J. D., & Prentice, R. L. (2002). *The Statistical Analysis of Failure Time Data*. Hoboken: John Wiley & Sons.

Kamakura, W. A., Wedel, M., de Rosa, F., & Mazzon, J. A. (2003). Cross-Selling Through Database Marketing: A Mixed Data Factor Analyzer for Data Augmentation and Prediction. *International Journal of Research in Marketing*, 20, 45-65.

Klein, J. P., & Moeschberger, M. L. (2003). *Survival Analysis: Techniques for Censored and Truncated Data*. New York: Springer.

Kuttner, R. (1998). The Net. A Market to Perfect for Profits. BusinessWeek. 3577**,** 20.

Lee, J. (2002). A Key to Marketing Financial Services: The Right Mix of Products, Services, Channels and Customers. *Journal of Services Marketing*, 16, 238-258.

Lee, J., & Marlowe, J. (2003). How Consumers Choose a Financial Institution: Decision-making Criteria and Heuristics. *International Journal of Bank Marketing*, 21, 53-71.

Levesque, T., & McDouglas, G. H. G. (1996). Determinants of Customer Satisfaction in Retail Banking. *International Journal of Bank Marketing*, 14, 12-20.

Levin, N., & Zahavi, J. (1996). Segmentation Analysis with Managerial Judgement. *Journal of Interactive Marketing*, 10, 28-47.

McKelvey, T. (2004). *Wake-Up Call: To Fix CRM, Fix the Customer Experience Now!* White Paper, McLean: Bearing Point.

Mittal, V., & Kamakura, W. A. (2001). Satisfaction, Repurchase Intent, and Repurchase Behavior: Investigating the Moderating Effect of Customer Characteristics. *Journal of Marketing Research*, 38, 131–142.

Mols, N. P. (1998). The Behavioral Consequences of PC Banking. *International Journal of Bank Marketing*, 16, 195-201.

Montoya-Weiss, M. M., Voss, G. V., & Grewal, D. (2003). Determinants of Online Channel Use and Overall Satisfaction with a Relational, Multichannel Service Provider. *Journal of the Academy of Marketing Science*, 31, 448-458.

Morgan, R. M., & Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, 58, 20-38.

Morrison, P. D., & Roberts, J. H. (1998). Matching Electronic Distribution Channels to Product Characteristics: The Role of Congruence in Consideration Set Formation. *Journal of Business Research*, 41, 223-229.

Mulhern, F. J. (1999). Customer Profitability Analysis: Measurement, Concentration, and Research Directions. *Journal of Interactive Marketing*, 13, 25-40.

Oliver, R. L. (1997). *Satisfaction: A Behavioral Perspective on the Consumer*. New York: McGraw-Hill.

Pfeifer, P. E., & Bang, H. (2005). Non-Parametric Estimation of Mean Customer Lifetime Value. *Journal of Interactive Marketing*, 19, 48-66.

Raijas, A., & Tuunainen, V. K. (2001). Critical Factors in Electronic Grocery Shopping. *International Review of Retail, Distribution and Consumer Research*, 11, 255-265.

Reichheld, F. (1993). Loyalty Based Management. *Harvard Business Review*, 71, 64-73.

Reichheld, F. (1996). *The Loyalty Effect*. Cambridge: Harvard Business School Press.

Reichheld, F., & Sasser, W. E. (1990). Zero Defections: Quality Comes to Services. *Harvard Business Review*, 68, 105-111.

Reichheld, F., & Schefter, P. (2000). E-Loyalty: Your Secret Weapon on the Web. *Harvard Business Review*, 78, 105-113.

Reinartz, W. J., & Kumar, V. (2000). On the Profitability of Long-Life Customers in a Non-Contractual Setting: An Empirical Investigation and Implications for Marketing. *Journal of Marketing*, 64, 17-35.

Reitsma, R., Omwando, H. K., Jackson, P., & Herzog, C. (2004). *The 2004 European Online Retail Consumer*. White Paper, Cambridge: Forrester Research.

Rosenbaum, P. R. (2002). *Observational Studies*. New York: Springer.

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70, 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *American Statistician*, 39, 33-38.

Rubin, D. B. (1979). Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational Studies. *Journal of the American Statistical Association*, 74, 318-328.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on Marketing: Using Customer Equity to Focus Marketing Strategy. *Journal of Marketing*, 68, 109-127.

Rust, R. T., & Zahorik, A. J. (1993). Customer Satisfaction, Customer Retention, and Market Share. *Journal of Retailing*, 69, 193-213.

Rust, R. T., Zahorik, A. J., & Keiningham, T. L. (1995). Return on Quality (RoQ). Making Service Quality Financially Accountable. *Journal of Marketing*, 59, 58-70.

Schaaf, J. (2005). *E-Banking Snapshot*. White Paper, Frankfurt: Deutsche Bank Research.

Schmittlein, D. C., Morrison, D., & Colombo, R. (1987). Counting Your Customers: Who Are They And What Will They Do Next. *Management Science*, 33, 1-24.

Shankar, V., Smith, A. K., & Rangaswamy, A. (2003). Customer Satisfaction and Loyalty in Online and Offline Environments. *International Journal of Research in Marketing*, 20, 153-175.

Sianesi, B. (2004). An Evaluation of the Active Labour Market Programmes in Sweden. *The Review of Economics and Statistics*, 86, 133-155.

Sinha, I. (2000). Cost Transparency: The Net's Real Threat to Prices and Brands. *Harvard Business Review*, 78, 43-50.

Smith, J. A., & Todd, P. E. (2005). Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators? *Journal of Econometrics*, 125, 305-353.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer Loyalty in E-Commerce: An Exploration of its Antecedents and Consequences. *Journal of Retailing*, 78, 41-50.

Stone, M., Hobbs, M., & Khaleeli, M. (2002). Multichannel Customer Management: The Benefits And Challenges. *Journal of Database Marketing*, 10, 39-52.

Thomas, J. S. (2001). A Methodology for Linking Customer Acquisition to Customer Retention. *Journal of Marketing Research*, 38, 262-268.

Thomas, J. S., & Sullivan, U. Y. (2005). Managing Marketing Communications with Multichannel Customers. *Journal of Marketing*, 69, 239-251.

Van den Poel, D., & Lariviere, B. (2004). Customer Attrition Analysis for Financial Services Using Proportional Hazard Models. *European Journal of Operational Research*, 157, 196-217.

Verhoef, P. C., & Donkers, B. (2005). The Effect of Acquisition Channels on Customer Loyalty and Cross-Buying. *Journal of Interactive Marketing*, 19, 31-43.

Vilcassim, N. J., & Jain, D. C. (1991). Modeling Purchase-Timing and Brand-Switching Behavior Incorporating Explanatory Variables and Unobserved Heterogeneity. *Journal of Marketing Research*, 28, 29-41.

Wallace, D. W., Giese, J. L., & Johnson, J. L. (2004). Customer Retailer Loyalty in the Context of Multiple Channel Strategies. *Journal of Retailing*, 80, 249-263.

Waller, W. T. (1988). The Concept of Habit in Economic Analysis. *Journal of Economic Issues*, 22, 113-126.

Watson, R. T., Akselsen, S., & Pitt, L. F. (1998). Attractors: Building Mountains in the Flat Landscape of the World Wide Web. *California Management Review*, 40, 36-43.

Wind, J., & Rangaswamy, A. (2001). Customerization: The Next Revolution in Mass Customization. *Journal of Interactive Marketing*, 15, 13-32.

Wright, C., & Sparks, L. (1999). Loyalty Saturation in Retailing: Exploring the End of Retail Loyalty Cards? *International Journal of Retail & Distribution Management*, 27, 429-440.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The Behavioral Consequences of Service Quality. *Journal of Marketing*, 60, 31-46.

Zhao, Z. (2004). Using Matching To Estimate Treatment Effects: Data Requirements, Matching Metrics, And Monte Carlo Evidence. *Review of Economics and Statistics*, 86, 91-107.

Beitrag 4

Measuring Perceived Channel Value (CHAVAL)

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Eingereicht zum

Journal of Retailing

Juni 2006

Measuring Perceived Channel Value (CHAVAL)

Abstract

Firms are increasingly utilizing non-store distribution channels to augment or possibly supplement existing product and service delivery processes. From a customer perspective, multi-channeling provides the opportunity to select their channel of choice. From a company perspective, multi-channeling poses new challenges. A variety of retail formats now compete with telephone, internet, and other channels as shopping environments. Consequently, understanding the factors that will lead customers to shop at one channel rather than another will become an important input to channel design and management. Despite some advances, knowledge of customer behavior in multi-channel environments is limited.

In this research project we therefore develop a 22-item scale, CHAVAL, that can be used to assess customer perceptions of channel value. Three distinct value dimensions emerge that are termed information stage, purchase stage, and transaction stage according to the different stages of the purchase process. Each value dimension again consists of several components such as perceived quality, convenience, risk, and price which determine the channel value at each stage of the purchase process. The CHAVAL scale has a variety of potential applications and can serve as a framework for further empirical research in this important area.

Keywords: Scale Development, Distribution Channel, Perceived Value

1 Introduction

The past decade has seen rapid and substantive changes in channels of distribution for goods as well as for services (Srinivasan, Anderson, & Ponnavolu 2002). Firms are increasingly utilizing non-store distribution channels to augment or possibly supplement existing product and service delivery processes (May & Greyser 1989; Alba et al. 1997; Geyskens, Gielens, & Dekimpe 2002; Schoenbachler & Goeffrey 2002). From a company perspective, multi-channeling poses new challenges. A variety of retail formats now compete with telephone, internet, and other channels as shopping environments (Balasubramanian 1998).

From a customer perspective, multi-channeling provides the opportunity to select their channel of choice (Wallace, Giese, & Johnson 2004). As a consequence, it is becoming common for customers to use different channels at different stages of the purchase process (Rangaswamy & Van Bruggen 2005). Some customers may use one channel to perform all shopping activities (Wallace, Giese, & Johnson 2004). Others may rely on different channels at different stages of the purchase process (Balasubramanian, Raghunathan, & Mahajan 2005). Consequently, understanding the factors that lead customers to use one channel rather than another will become an important information for channel design and management (Black et al. 2002).

The paper by Alba et al. (1997) argues that customers choose the channel which provides the highest value to them in a given situation. If it is true that customers are "value-driven" (Levy 1999), then managers need to understand what customers value in a specific channel. Although customer perceptions of channel value are considered pivotal determinants of channel choice behavior, there has still been no empirical research to develop an in-depth understanding of this concept (Forsythe et al. 2006). Hence, no research has focused on specifying the domain or on developing a practical and applicable scale to measure perceived channel value.

The aim of this paper is to develop, refine, and evaluate a multi-item scale for measuring perceived channel value (CHAVAL). The scale development process involves a sequence of steps consistent with conventional guidelines for scale development (Churchill 1979; Peter 1979; Peter 1981; Gerbing & Anderson 1988; Rossiter 2002). Figure 1 provides an overview of the steps.

Figure 1: Process Employed in Developing the Scale to Measure Perceived Channel Value

Step 1: Specify concept of perceived channel value.

Step 2: Develop an initial set of items.

Step 3: Collect data – first data set.

Step 4: Develop a purified scale through an iterative process.

Step 5: Collect data – second data set.

Step 6: Assess robustness of channel value scale.

The remainder of this article is organized as follows. First we provide a synopsis of the existing literature on the concept of perceived channel value. Drawing on insights from the literature and a comprehensive qualitative study, the domain of perceived channel value is delineated and a preliminary scale is developed. The next sections describe the data collection and refinement of the preliminary scale. After developing and testing a scale to measure perceived channel value, its robustness is examined. We therefore collect a second data set and evaluate the scale's reliability and validity again. We conclude the article by stating theoretical and managerial implications and the limitations of our study.

2 The Concept of Perceived Channel Value

Zeithaml (1988, p.14) suggests that perceived value of a product can be regarded as a "*consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given*". She refers to this assessment as a comparison of a product's get and give components. A common such definition of value is the trade-off between the quality and price of a product (Monroe 1990). Other authors suggest that viewing product value as a trade-off only between quality and price is too narrow (Bolton & Drew 1991). Anderson, Jain, & Chintagunta (1993) for instance, define value as the complete set of a product's attributes received by a customer in exchange for a price paid. Yet others define the give components as not only the money expended but also the time and effort spent in acquiring the product (Zeithaml 1988). Despite the multiplicity of definitions some commonalities exist. Perceived value can be defined as a trade-off between what the customer receives (e.g. quality, benefits) and what she gives up to acquire and use a product (e.g. price, transaction cost) (Woodruff 1997; Parasuraman & Grewal 2000).

This basic concept can also be applied to determining the customer's perceived value of a distribution channel (Parasuraman, Zeithaml, & Berry 1985; Parasuraman, Zeithaml, & Berry 1988). Similarly to products, channels offer benefits and generate costs when using them. Hence, perceived value represents the net gain from using a specific channel (Reardon & McCorkle 2002).

Measuring channel value requires therefore to identify the benefits and costs perceived by a customer when using a channel. Two streams of literature allow to identify these benefits and costs: (i) the perceived customer value literature and (ii) channel choice literature.

The customer value literature addresses the multi-dimensional nature of the perceived value construct. Although no empirical research on the pivotal components related to channel value has been reported, the literature formulates some hypotheses about channel value (Zeithaml 1988). Bishop (1984) for example, claims that value is a composite of quality and price in a retail setting. Similarly, it can be argued that the quality and the price structure offered by a channel influences the perceived value of the channel. Doyle (1984) identifies convenience combined with quality and price as factors producing channel value perceptions. As a consequence, it can be assumed that the convenience of using a channel positively impacts the value of a channel. Finally, Sweeney, Soutar, & Johnson (1999) show that perceived risk has an impact on the value perception of customers. Perceived risk is considered to negatively influence perceived value. Summing up, the review of the perceived customer value literature suggests four components for the channel value construct: perceived quality, convenience, risk, and price.

The second stream of research which provides insights into the components of perceived channel value is the channel choice literature. The channel choice literature aims at modeling the choice behavior of customers in a multi-channel environment based on the concept of utility maximization (Thomas & Sullivan 2005). Thus, factors identified by the channel choice literature as influencing channel choice and hence a channel's utility can also be regarded as components of channel value.

The existing channel choice literature identifies a large number of factors which are not combined naturally into cohesive groups (e.g. Childers et al. 2001; Kaufman-Scarborough & Lindquist 2002; Gupta, Su, & Walter 2004). Instead, some factors have the same meaning but are labeled differently. In other cases channel attributes rather than benefits or costs are identified. However, summarizing the channel choice literature also leads to the four components of channel value:

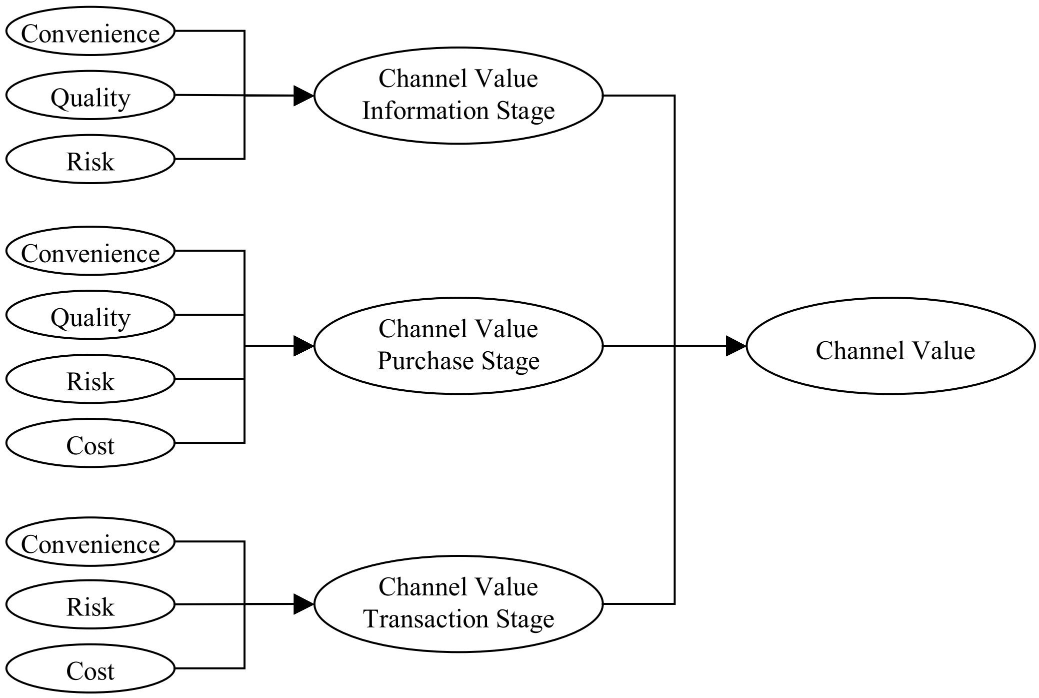
- perceived quality of the service provided by the channel (Tse & Yim 2001; Montoya-Weiss, Voss, & Grewal 2003),
- perceived convenience offered by the channel (Keeney 1999; Tse & Yim 2001; Black et al. 2002; Dholakia & Uusitalo 2002; Grewal, Levy, & Marshall 2002; Reardon & McCorkle 2002; Srinivasan, Anderson, & Ponnavolu 2002; Devlin & Yeung 2003),
- perceived risk involved in conducting transactions through the channel (Black et al. 2002; Grewal, Levy, & Marshall 2002; Reardon & McCorkle 2002; Schoenbachler & Goeffrey 2002; Devlin & Yeung 2003; Montoya-Weiss, Voss, & Grewal 2003), and
- perceived price of conducting business through the channel (Tse & Yim 2001; Black et al. 2002; Devlin 2002; Grewal, Levy, & Marshall 2002; Reardon & McCorkle 2002; Fader, Hardie, & Lee 2003).

Hence the review of the channel choice literature produces the same components of channel value as the review of the perceived value literature. The channel value construct is therefore hypothesized to consist of four components: perceived quality, perceived convenience, perceived risk, and price of using a channel.

Yet the identified components are not equally relevant across different situations. Holbrook & Corfman (1985) postulate, for example, that value perceptions are situational and hinge on the context within which an evaluative judgment occurs. As a consequence, emerging evidence supports the idea that customers perceive value differently as they go through the different stages of the purchase process (Gradial et al. 1994). For example, customers may consider somewhat different attributes when using a channel for information search rather than purchasing (Oliver 1997). Hence we consider the following three dimensions of perceived channel value: the channel value at the information stage, the purchase stage, and the transaction stage. Following the argumentation by Sheth, Newman, & Gross (1991) these three stage-specific channel values are independent and add up to overall channel value (see Figure 2).

The preceding paragraphs provide a conceptual framework for a measure of perceived channel value. Customers' overall assessment of channel value can be decomposed into three dimensions: channel value at the information, the purchase, and the transaction stage of the purchase process. As these three dimensions are independent of each other, they can be combined in a formative manner to measure channel value. Each dimension consists again of multiple components of which each might be a higher level construct such as perceived quality, convenience, risk, and price. Measuring the stage-specific channel value dimensions is achieved by combining the relevant components as well in a formative manner. The components, on the other hand, can be measured in a reflective manner.

Figure 2: Channel Value Construct



3 Development of an Initial Set of Items

In order to develop an initial set of items we first explore the ideas that customers hold about channel value (see Figure 1). We therefore conduct one focus group consisting of 6 participants who are between 25 to 35 years of age. Participants have to use multiple channels regularly to interact with a firm, as the key purpose of this session is to generate items measuring channel value across different channels.

When asked about channel value, participants tend to think of specific channel attributes. For example, the opening hours of a channel and the time needed to conduct a business through a channel are some of the attributes mentioned by the participants. Subsequently, participants are asked why these aspects are important to them in an attempt to better understand the underlying benefits. After some generic items are generated to measure channel value, specific channels are discussed to stimulate participants to think in different directions.

To enrich the items generated by the participants in the focus group, we conduct a second literature review (Selltiz, Wrightsman, & Cook 1976; Fink 2003). The literature review aims to identify existing marketing scales measuring the different components of channel value such as perceived quality, convenience, risk, and price. These scales can then be adapted to suit the context of channel value. The two scales developed by Rugimbana & Iversen (1994) and Dabholkar, Thorpe, & Rentz (1996) to measure perceived quality are deemed appropriate to enrich the list of perceived quality items generated by the focus group. Both these scales not only measure perceived quality, but include items for the perceived convenience of a channel as well. In addition, the scale developed by Parasuraman, Zeithaml, & Berry (1994) includes additional items which can be adapted to measure the convenience of a channel. Items which measure the perceived risk while using a channel are created by following the scoring approach described by Cunningham (1967) and by adapting the scale developed by Sweeney, Soutar, & Johnson (1999). Based on transaction cost theory (Williamson 1985) and the scale devised by Sweeney & Soutar (2001), we develop items to measure the perceived price construct. After accounting for identical and equivalent items, a total of 71 channel value statements are retained for further evaluation.

Finally, 14 marketing experts evaluate the items obtained from the focus group and the literature review to ensure they are representative of the scale's domain. The use of experts as judges of a scale's domain is commonly used in marketing (Zaichowsky 1985; Babin & Burns 1998). To assist, we give each judge a description of each of the dimensions and components of channel value identified. In addition, judges are asked to evaluate the wording and the comprehensibility of the items. An a-priori item-retention decision rule is used whereby only items which at least ten of fourteen judges classify as highly representative of a specific value component are retained (Bearden, Netemeyer, & Teel 1989). In addition, items have to be unambiguous. This results in 41 of the 71 items originally assessed being retained as the initial basis for a perceived value scale.

4 Data Collection – First Data Set

The next stage of the scale development process is the data collection step. The data collected provides the basis for the quantitative analysis of the initial scale measuring perceived channel value. We therefore develop a questionnaire consisting of three sections. The first section is designed to provide a profile of the respondent. Thus, we include some demographic and behavioral variables such as age, gender, and channel usage. The second section of the questionnaire asks respondents to state their overall value perception of a specified channel. The third section of the questionnaire is designed to evaluate a channel based on the items from the initial scale. The wording of the initial items is modified to measure the channel value for a specific stage in the purchase process. The channel value at the information stage is measured by 32 items, the purchase stage by 41 and the transaction stage by 38 items. The number of items per stage of the purchase process varies due to different operationalization. For instance, the price construct is omitted at the information stage as provisions of product information and product consultations are usually provided free. The minor difference in the number of items for the purchase and the transaction stage is due to a different operationalization of perceived price.

Six distinct versions of the questionnaire are developed to reduce the effort for the respondents. Sections one and two are consistent across all six versions of the questionnaire. Section three varies by the channel and the stage of the purchase process being considered. One half of the respondents evaluates the brick-and-mortar channel, whereas the other half has to rate the internet channel. We restricted the first data collection to these two channels as they are by far the most prominent channels in the market, which ensures a high response rate. Each half of the respondents is again divided in three groups. Each of these groups has to evaluate a channel for one specific stage in the purchase process. All statements are designed to be answered by a 5-point Likert scale ranging from 1 (I strongly disagree) to 5 (I strongly agree).

The questionnaire is administered to postgraduate students and a total of 434 students respond to the questionnaire and are used as basis for the quantitative analysis.

5 Exploratory Investigation of Dimensionality

In the case of reflective constructs, some researchers suggest performing an exploratory factor analysis as a starting point of the quantitative analysis to identify the components underlying the dimensions of the construct (Churchill 1979). An exploratory factor analysis is therefore performed for each of the 3 dimensions of the channel value construct and is used to purify the preliminary scales. Thus items which can not be assigned clearly to a specific component are eliminated. As criteria to determine the appropriate number of components extracted, we use Eigenvalues and interpretability (Hair et al. 2005, p.120).

The exploratory factor analysis for the information stage leads to 4 components. They could be interpreted as perceived quality, perceived risk, time convenience, and ease of use (see Table 1).

Table 1: Exploratory Investigation of Dimensionality – First Data Set – Information Stage

Item	Quality	Risk	Time conv.*	Ease of use
The information offered on this channel answers all my questions.	0.6117			
On this channel I receive individualized information.	0.7067			
The information offered on this channel satisfies all my needs.	0.6192			
The information offered on this channel increases my trust.	0.6067			
Error free consultation is guaranteed on this channel.	0.5212			
The perceived quality of consultation on this channel is constantly good.	0.5944			
Problems arising when using this channel are resolved quickly.	0.7417			
This channel offers a good service when I need it.	0.7546			
I perceive the channel not to be suited to seeking information.	0.6185			
The service offered on this channel meets my expectations.	0.5580			
The information offered meets my expectations.	0.6489			
The information offered on this channel is exactly what I am looking for.	0.6867			
Seeking information using this channel involves low risk.		0.5664		
Information search on this channel involves higher risk compared to others.		-0.7040		
When using this channel I am worried this will not be advantageous.		-0.7169		
I feel safe when seeking information using this channel.		0.6229		
I am not worried that I will be involved in something risky when using this		0.6669		
On this channel the likelihood of receiving bad consultation is especially…		-0.5440		
This channel allows one to search for information at any time.			0.7311	
I need a lot of time to search for information on this channel.			-0.6211	
I am flexible about when I search for information through this channel.			0.8072	
I need only a little time to search for information on this channel.			0.6973	
The channel design eases the search for information.				0.5862
It is easy to seek information on this channel.				0.8228
This channel offers me a lot of convenience when seeking information.				0.6100
Seeking information on this channel is very troublesome.				-0.5633
This channel might provide particularly bad advice.	-0.5326	-0.5631		
This channel offers a low quality service.	-0.5723	-0.5259		
This channel allows me to search for information in a user-friendly way.	0.5863			
Information is always provided in time by this channel.				
Seeking information on this channel requires little effort.			0.5748	0.6196
Seeking information on this channel is very inconvenient.				

Note: All loadings below 0.5 have been suppressed; Conv. = Convenience

While even time convenience and ease of use are sometimes combined in one construct, the exploratory factor analysis for the information stage elicits two distinct components. This component structure emphasizes the distinctiveness of time elapsed for finding the relevant information searched for and the usability of the channel. 26 items show high loadings (>0.50) for one specific component. The remaining 6 items can either not be assigned to one specific component, are mis-formulated, or do not show any loadings above the cut off point (0.50). We therefore reduce the scale for the channel value in the information stage to 26 items.

The estimation results for the purchase stage also suggest a 4 component solution. We extract components for perceived quality, risk, convenience, and price. In this case all items load highly on either one of the components. Only two items are excluded from the further scale development process due to low correlations to the components. The scale for the purchase stage is left with 39 items (see Appendix A).

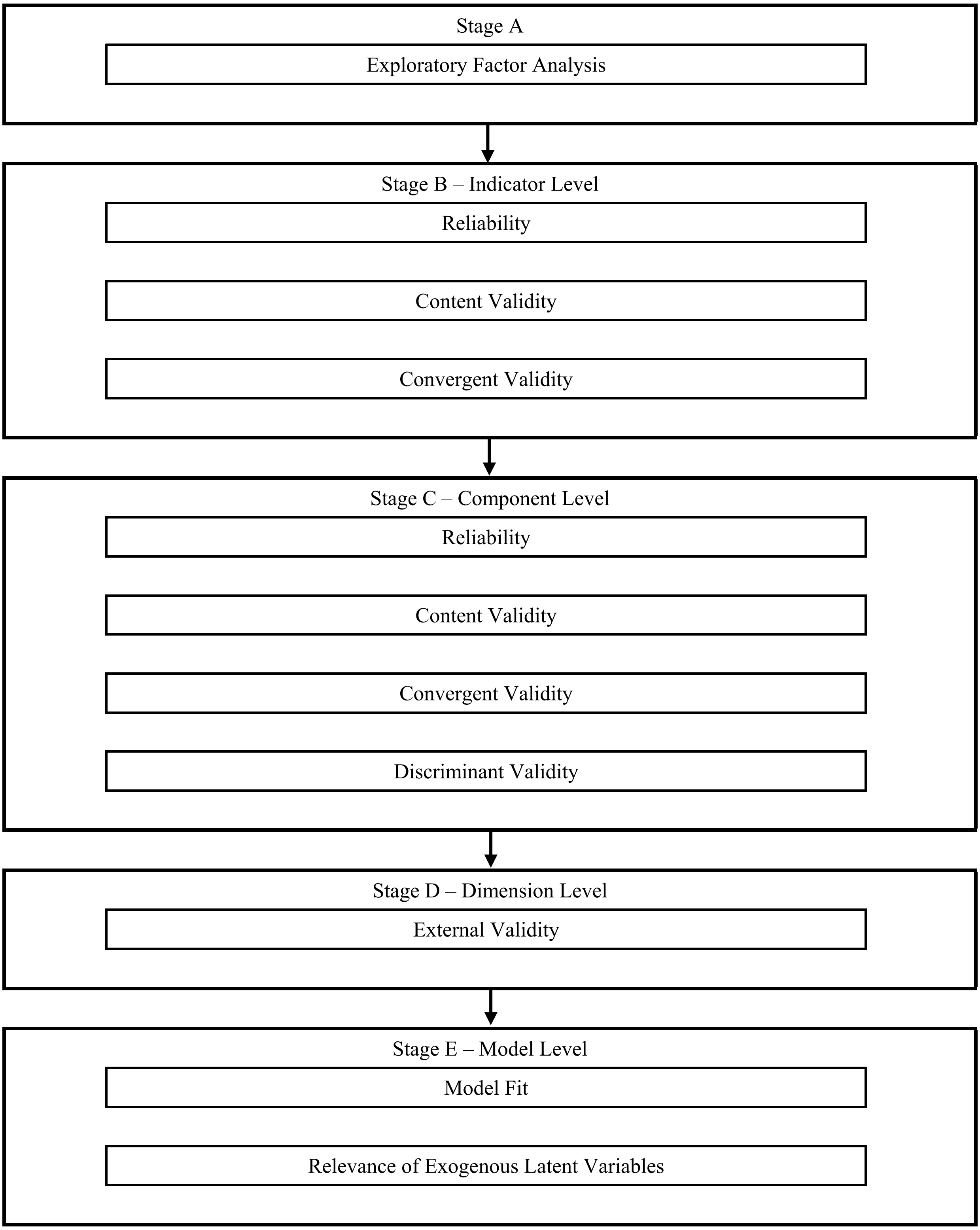
At the transaction stage three components are extracted. These can be described as a combined quality-convenience, a risk, and a price component. The number of items is reduced by one due to ambiguous loadings. 9 additional items are excluded from the scale due to low loadings (<0.50). After eliminating these 10 items, 28 items are still available to measure the channel value in the transaction stage (see Appendix B).

6 Evaluating the Reliability and Validity of the Channel Value Scale – First Data Set

Evaluating the reliability and validity of the channel value scale is a stepwise process. To test for the reliability and validity of a multi-dimensional scale, each level of the construct has to be evaluated. The preliminary channel value scale consists of four levels: the indicator, the component, the dimension, and the model level (see Figure 3).

The indicator reliability investigates how much of an item's variance can be explained by the underlying latent variable. The literature suggests two approaches to investigating the reliability of the items. First, by determining the relevant factor loadings. The literature suggests that loadings of 0.70 or higher are reliable (Bagozzi & Baumgartner 1994). This cut off value is justified by the fact that at least 50 percent of an item's variance should be explained by the underlying latent variable (Carmines & Zeller 1979). Similar to this approach, Fornell & Larcker (1981) suggest comparing the squared loadings with the error variance.

Figure 3: Process Employed for the Quantitative Analysis



(1) $$\rho_y = \frac{\lambda_y^2}{\lambda_y^2 + \mathrm{Var}(\varepsilon_y)}$$

ρ_y : indicator reliability of the item for latent variable y,
λ_y : loading of the item for latent variable y,
ε_y : measurement error of the item for latent variable y.

An item appears to be reliable in the case of an indicator reliability above 0.40. Both related approaches require the estimation of a confirmatory factor analysis. We therefore conduct a confirmatory factor analysis for each stage in the purchase process. The estimation results for the information stage suggest that 9 items should be eliminated. The cut-off value of 0.70 for the loadings was not reached by two items for the risk component, by three items for the convenience component, and four items for the quality component (see Table 2). These eliminations are confirmed by the measure of indicator reliability developed by Fornell & Larcker (1981). After excluding those items, the risk component for the information stage consists of four items, the convenience component of five items, and the quality component of eight items.

The results for the purchase stage suggest only some minor eliminations. None of the two approaches to testing the indicator reliability postulates the elimination of an item for the convenience component. Only the elimination of two items in the quality component and three items in the risk and the price component are suggested (see Appendix C).

The estimation of the transaction stage produces very low loadings for the risk component. Only two of the items receive loadings above 0.70. Hence, the remaining 9 items are eliminated, especially as the indicator reliability supports this elimination. The eliminations for the price and the convenience component are small. Only two items in both the convenience and the price component are excluded from the further scale development process (see Appendix D).

Table 2: Results of Confirmatory Factor Analysis – First Data Set – Information Stage

Item	Loading	Indicator Reliability	T-Value
Quality			
The information offered on this channel answers all my questions.	0.7306	0.5338	14.7487
On this channel I receive individualized information.	0.7014	0.4920	11.4190
The information offered on this channel satisfies all my needs.	0.7964	0.6342	20.1965
The information offered on this channel increases my trust.	0.7628	0.5819	17.7949
Error free consultation is guaranteed on this channel.	0.5188	0.2691	6.2732
I perceive the quality of consultation on this channel is constantly…	0.6852	0.4695	13.7276
Problems arising when using this channel get resolved quickly.	0.6769	0.4582	10.1224
This channel offers a good service when I need it.	0.7444	0.5541	19.6701
I perceive the channel not to be suited to seeking information.	0.6820	0.4651	12.7580
The service offered on this channel meets my expectations.	0.7322	0.5361	17.2178
The information offered meets my expectations.	0.7438	0.5532	18.5851
The information offered on this channel is exactly what I am…	0.8112	0.6581	30.1163
Convenience			
The channel design eases the search for information.	0.7100	0.5040	2.1978
It is easy to seek information on this channel.	0.7041	0.4958	2.1894
This channel offers me a lot of convenience when seeking…	0.7284	0.5306	2.2191
Seeking information on this channel is very troublesome.	-0.7141	0.5099	2.1259
This channel allows one to search for information at any time.	0.6049	0.3659	1.7482
I need a lot of time to search for information on this channel.	-0.5441	0.2960	1.8671
I am flexible about when I search for information through this…	0.6552	0.4293	1.9013
I need only a little time to search for information on this channel.	0.7231	0.5229	2.2555
Risk			
Seeking information using this channel involves low risk.	0.6507	0.4234	1.0255
Information search on this channel involves higher risk compared…	-0.7461	0.5567	1.0220
When using this channel I am worried this will not be advantageous.	-0.7779	0.6051	1.0294
I feel safe when seeking information using this channel.	0.7793	0.6073	1.0309
I am not worried that I will be involved in something risky when…	0.6958	0.4842	1.0357
On this channel the likelihood of receiving bad consultation is…	-0.7135	0.5090	1.0161

To evaluate the indicator validity only the content and the convergent validity can be tested. The content validity is examined by checking the estimation results for their plausibility. The loadings estimated by the confirmatory factor analysis all show the expected direction. Hence all results appear to be plausible and fulfill the requirements of content validity. The convergent validity of the items can be determined by testing the significance of the loadings (Gerbing & Anderson 1988; Bagozzi, Yi, & Phillips 1991). Thus, we investigate whether the loadings of the items are significantly different from zero. After applying bootstrapping procedures, all estimation results show a significant difference from zero at a 5 percent level except for the items measuring perceived risk and price at the information and purchase stage (see Table 2 and Appendix C). The t-values for perceived risk and price across these two stages range between 1.00 and 1.38. This indicates no significant impact of perceived risk and price on channel value at the information and purchase stage. Standard literature on scale development suggests excluding items which do not fulfill the requirements for convergent validity from the further scale development process. As a consequence, the corresponding risk and price measures would have to be eliminated. In contrast to the standard procedure we retain the items measuring perceived risk and price. Our decision is motivated by the following rationale: The channel choice literature views perceived risk and price as playing a pivotal role in a channel's perception. Perceived risk and price are therefore major components of channel value as identified by the literature. One explanation for the insignificant impact of perceived risk could be the sample used in our study. All respondents of the first data set are students. But earlier research has shown perceived risk to play a less important role for younger consumers (Zeithaml & Gilly 1987; Lee & Tan 2003). The insignificant impact of the price measures might be due to the fact that the sample used in our study is not aware of any price differences between different channels. The elimination of the perceived risk and price construct should therefore await cross-validation using a second data set.

In addition, Hansen (1987) argues that even insignificant items with t-values above 1.00 still have an impact on the endogenous variable. Thus, only items with t-values below 1.00 should be eliminated.

The second stage of the model evaluation is concerned with testing the reliability and validity of the components. The reliability of the components can be investigated using two approaches both suggested by Fornell & Larcker (1981). First the shared variance of the measurement model should be examined in terms of its composite reliability:

(2) $$\rho_\eta = \frac{\left(\sum_{n=1}^{N} \lambda_{y,n}\right)^2}{\left(\sum_{n=1}^{N} \lambda_{y,n}\right)^2 + \sum_{n=1}^{N} \mathrm{Var}(\varepsilon_n)}$$

ρ_η : reliability of component/latent variable η,
$\lambda_{y,n}$: loading of item n for latent variable y,
ε_n : measurement error of item n.

The reliability of the component is given for a composite reliability larger than 0.60 (Bagozzi & Yi 1988). But as this approach does not measure the amount of variance that is captured by the latent variable in relation to the amount of variance due to measurement error, the average variance extracted was suggested as a second reliability measure. It can be calculated by:

(3) $$\rho_{vc(\eta)} = \frac{\sum_{n=1}^{N} \lambda_{y,n}^2}{\sum_{n=1}^{N} \lambda_{y,n}^2 + \sum_{n=1}^{N} \mathrm{Var}(\varepsilon_n)}$$

$\rho_{vc(\eta)}$: average variance extracted of component/latent variable η.

If $\rho_{vc(\eta)}$ is less than 0.50, the variance due to measurement error is larger than the variance captured by the latent variable, and the reliability of the items and the latent variable is questionable (Fornell & Larcker 1981). The estimation results indicate that across all components of the channel value construct the composite reliability is always above 0.60 and the average variance extracted always above 0.50. Thus the reliability of the various components of the channel value scale has been proven (see Table 3).

After the reliability of the components has been tested, it is necessary to evaluate the validity of the components as well. This can be achieved by testing the content, the convergent, and the discriminant validity of the different components (Bohrnstedt 1970; Bagozzi & Phillips 1982).

Table 3: Composite Reliability and Average Variance Extracted – First Data Set

Component	Composite Reliability	AVE
Information		
Quality	0.9082	0.5861
Risk	0.8464	0.5796
Convenience	0.8751	0.6371
Purchase		
Convenience	0.9364	0.6218
Price	0.7302	0.5751
Risk	0.8833	0.6031
Quality	0.9131	0.5680
Transaction		
Risk	0.7559	0.5080
Convenience	0.9398	0.6352
Price	0.7996	0.5711

The content validity of the component level can be examined in the same manner as was done for the indicator level. The direction of the estimated effect has to be plausible. An evaluation of the estimated loadings reveals that all results appear to be as hypothesized and are therefore plausible. The convergent validity of a component is fulfilled if the composite reliability is above 0.60 (Bagozzi & Yi 1988). As was already shown for the reliability testing, all the values of the proposed perceived channel value construct are above 0.60. This result shows that the items of a specific component are strongly related to each other and therefore measure the same component. The average variance extracted can be used not only to evaluate the reliability of a component, but also to test its discriminant validity. To fully satisfy the requirements for discriminant validity, the average variance extracted for each latent variable should be greater than all squared correlations between the latent variables of the model (Fornell & Larcker 1981). The highest correlation between the latent variables of the model was 0.45 between perceived risk and quality in the information stage. This value is still below the average variance extracted for all components of the model. These results support the hypothesis of distinct components included in the model, even when considering measurement error (Fornell & Larcker 1981).

The third level of the proposed channel value scale consists of three dimensions. Each dimension represents one stage in the purchase process. Each of these stages again consists of several components contributing to the value of a channel within a specific stage of the purchase process. The dimensions of the construct have been operationalized as emergent constructs, since the components additively contribute to the stage-specific channel value. Unlike latent constructs, measures of emergent constructs are not required to covary. Traditional test criteria for examining the reliability and validity are therefore not applicable (Fornell & Larcker 1981; Hulland 1999). Emergent constructs can only be evaluated by their external validity (Mathieson, Peacock, & Chin 1996; Hulland 1999; Rossiter 2002; Reinartz, Krafft, & Hoyer 2004).

It is often possible to operationalize an emergent construct in a reflective and a formative manner. Combining some reflective and formative items allows us to estimate a multiple-indicators and multiple-causes (MIMIC) model (Hauser & Goldberger 1971). External validity can be confirmed if the overall model fit proves acceptable (Diamantopoulos & Winklhofer 2001). The R-square which can be used as a measure of model fit ranges between 0.70 and 0.79 for all three MIMIC models. The model fit can therefore be deemed appropriate and the external validity of the three dimensions can be supported.

The fourth level of the channel value construct is concerned with the overall model. The overall model is evaluated by the percentage variance (R-square). It measures how well the estimated regression function fits with the underlying manifest variables (Hair et al. 2005, p.237). The R-square of the proposed model is 0.25, which is an acceptable value for empirical studies (Lattin, Carroll, & Green 2003, p.53).

But the goodness of a model cannot be evaluated solely by how well the model fits the data. In addition it is necessary to determine whether all exogenous latent variables contribute significantly to explaining the endogenous latent variable. Two different criteria have been proposed to test for this significant contribution (Chin 1998). One approach is to examine the path coefficients for plausibility and significance. The plausibility of the path coefficients can be tested analogously to a regression model as the path coefficients represent the counterpart to standardized beta coefficients. Our estimation results show that all path coefficients are plausible and also highly significant. Another measure for evaluating the contribution of the exogenous latent variable is the F-square statistic developed by Chin (1998). The F-square can be calculated as follows:

$$F^2 = \frac{R^2_{incl} - R^2_{excl}}{1 - R^2_{incl}} \quad (4)$$

R^2_{incl}: R-square of the model including all exogenous latent variables,
R^2_{excl}: R-square of the model excluding one of the exogenous latent variables.

The values for the information, the purchase, and the transaction stage are 0.07, 0.12, and 0.14 respectively. These values indicate a medium contribution of each of the exogenous latent variables (Cohen 1988; Chin, Marcolin, & Newsted 2003). After having reviewed the R-square, the path coefficients, and the F-square we can deem the overall fit of the model acceptable and approve the three dimensions of the channel value construct.

The final step required to assess the reliability and validity of the scale requires us to test for multicollinearity among the measures that form an emergent construct. To test for multicollinearity we review the pairwise correlations between the measures of an emergent construct. The results indicate that none of the correlations reaches a critical level (>0.50).

Although these results provide evidence of the reliability and validity of the scale developed, the results are based on a student sample. The scale is therefore re-examined using an independent and more diverse data set, as recommended by Churchill (1979).

7 Data Collection – Second Data Set

A second empirical study is conducted to test the reliability and validity of the perceived channel value scale developed. Once more respondents are asked to evaluate several channels using the channel value scale. We used the primary channels available in the banking industry for evaluation, given its long history of multi-channeling. This suggests a reasonable degree of familiarity with multiple channels among banking customers (Hitt & Frei 2002).

The questionnaire is structured in two parts. The first group of questions related to the respondent's demographics and their usage behavior in terms of banking products, banking institutions, and banking channels. These questions are intended to profile the respondent and to ensure that all customers are active multi-channel users. The second group of questions is intended to measure the perception of the branch, the internet, the call center, and the banking terminal. The respondents' perception of each channel is measured by the perceived channel value scale developed above. The respondents are asked to evaluate the overall channel value along all items of the scale developed. Hence, the respondents have to determine their perceived value for all four channels across all three stages of the purchase process. In total the respondents have to reply to 63 items of which 17, 31, and 15 measure channel value at the information, the purchase, and the transaction stage respectively. As in the first empirical study the items are administered as 5-point Likert scales ranging from 1 (I strongly disagree) to 5 (I strongly agree).

In a first step we pre-test the questionnaire for its applicability by using a group of selected banking customers. Most respondents criticize the length of the perceived channel value scale developed. They question whether many respondents would be willing to use all 63 items to measure the perceived channel value. We therefore decide to further reduce the number of items used to measure the perceived channel value. As each latent variable is measured by multiple items, we decide to eliminate items which are closely correlated. The item elimination proceeds under the condition that the reliability and validity of the measured latent variable does not decrease. Furthermore, multi-item measurement for each latent variable has to be maintained. Following this procedure, we are able to decrease the number of items measuring the perceived channel value to a total of 24 items. The reliability and validity of the new 24 item scale to measure perceived channel value is now tested by using a second data set.

8 Assessing the Robustness of the Channel Value Scale – Second Data Set

We conduct an empirical study among randomly selected German banking customers who use multiple banking channels. A total of 500 customers participate in the study. Each customer is interviewed face-to-face to ensure a clear understanding of the purpose of the study and of the questionnaire.

The main objective of the second stage is to evaluate the robustness of the 24 item scale intended to measure perceived channel value. The procedure involves several steps, similar to those used with the first data set.

We start again by examining the reliability and validity of the proposed scale at the indicator level. The estimation results of the confirmatory factor analysis for the information stage indicate that the reliability and validity of all items can be supported. Even the items measuring the risk and price construct show significant t-values unlike the results of the first data set. The final scale used to measure the perceived channel value at the information stage consists of three items measuring perceived quality and convenience and two items measuring perceived risk (see Table 4).

The criteria for reliable measures in the purchase stage are met by all items except one. One item measuring convenience produced a factor loading which is below the hurdle rate of 0.70. We therefore eliminate this item which leaves two items to measure convenience at the purchase stage. Examining the direction of effects and the t-values of the items measuring perceived channel value at the purchase stage reveals only plausible and significant results.

Table 4: Results of Confirmatory Factor Analysis – Second Data Set

Item	Loading	Indicator Reliability	T-Value
Information			
Quality			
The information offered on this channel satisfies all my needs.	0.8869	0.7867	140.8989
The information offered meets my expectations.	0.9348	0.8738	287.6399
On this channel I receive individualized information.	0.8599	0.7394	119.1588
Convenience			
The channel design eases the search for information.	0.9413	0.8861	290.6841
This channel offers me a lot of convenience when seeking…	0.9428	0.8890	313.1496
Risk			
I feel safe when seeking information using this channel.	0.9297	0.8644	436.0241
Information search on this channel involves higher risk…	-0.8561	0.7329	81.7013
Purchase			
Quality			
The products offered meet my expectations.	0.9146	0.8364	190.4704
The products offered on this channel are exactly what I am…	0.9174	0.8416	202.6168
The products offered on this channel satisfy all my needs.	0.9367	0.8774	298.4839
Convenience			
Purchasing products on this channel requires little effort.	0.8223	0.6761	13.0238
Purchasing products on this channel is very troublesome.	-0.2441	0.0596	1.6590
I am flexible about when I purchase products through this channel.	0.9025	0.8146	26.7661
Risk			
On this channel the likelihood of a wrong purchase is especially…	0.9499	0.9023	6.5095
On this channel I am especially likely to get a product purchase…	0.9364	0.8768	6.4370
Price			
I might purchase products at an inflated price on this channel.	0.8921	0.7958	10.8895
The prices offered on this channel are higher than on other…	0.8869	0.7866	11.4593
Transaction			
Convenience			
The channel design eases the execution of transactions.	0.9356	0.8753	289.3710
It is easy to conduct transactions on this channel.	0.9429	0.8890	294.1185
I need only a little time to conduct transactions on this channel.	0.8472	0.7178	96.4234
Risk			
I feel safe when conducting transactions through this channel.	0.9886	0.9773	88.1504
When using this channel I am worried this will not be…	-0.4981	0.2481	5.9727
Price			
The prices offered on this channel are higher than on other…	0.9017	0.8130	6.2932
The fees for using this channel are higher than on other channels.	0.9509	0.9041	6.5823

This leaves a scale including nine items of which convenience, price, and risk are each measured by two items and quality by three items.

The confirmatory factor analysis of the items measuring the perceived channel value in the transaction stage identifies one item measuring perceived risk with a loading of only -0.50. According to the criteria for reliable measures, the feasible approach would be to eliminate this item. However, this elimination would produce a single item measure for the perceived risk in the transaction stage with all its negative consequences such as a considerable amount of measurement error (Churchill 1979). Nevertheless, we decide to eliminate the item in question. Our decision is based on the estimation results of the confirmatory factor analysis. They indicate a large measurement error for the perceived risk construct if the item is included in the scale. The elimination of this item produces a valid scale measuring perceived channel value at the transaction stage. The final scale consists of six items measuring perceived risk, price, and convenience by one, two, and three items respectively.

The second stage of the model evaluation is concerned with the reliability and the validity at the component level. The results presented in Table 5 represent the composite reliability and the average variance extracted from all the components of the perceived channel value construct. All components show values for the composite reliability and the average variance extracted which are clearly above the hurdle rate of 0.60 and 0.70 respectively. Thus the reliability of the items measuring the components can be supported by these results. Similarly, the convergent validity of the components can be confirmed, as the composite reliability measure clearly exceeds the value of 0.60. The values for the average variance extracted, ranging from 0.75 to 0.98, also exceed the highest squared correlation between the latent variables of 0.71. This confirms the discriminant validity of the scale developed at the component level.

The third level of the perceived channel value construct consists, as in the case of the first data set, of three dimensions representing the three stages of the purchase process. Again these dimensions are operationalized as emergent constructs. For this reason we examine only the external validity of the construct using formative and reflective measures simultaneously. The reflective operationalization of the emergent constructs is accomplished by re-using the items developed to measure the components of the corresponding dimension (Lohmöller 1989). All three dimensions show a high level of external validity which supports the proposed dimensionality of the perceived channel value construct.

Table 5: Composite Reliability and Average Variance Extracted – Second Data Set

Component	Composite Reliability	AVE
Information		
Quality	0.9230	0.7999
Risk	0.8879	0.7986
Convenience	0.9404	0.8875
Purchase		
Convenience	0.8538	0.7453
Price	0.8834	0.7912
Risk	0.9415	0.8895
Quality	0.9452	0.8518
Transaction		
Risk	0.9773	0.9773
Convenience	0.9348	0.8274
Price	0.9239	0.8586

The fourth level of the scale evaluation is concerned with the overall model. In the case of the second data set we evaluate the overall model by determining the significance and plausibility of the path coefficients as well as by calculating the F-square statistic. As we are re-using the measures of the indicator level in order to operationalize the channel value construct, using the R-square to evaluate the overall model is not feasible in this case (Lohmöller 1989).

The path coefficients of the model are all highly significant and show a plausible direction of the measured effects (see Table 6). A similar picture is drawn by using the F-square statistic developed by Chin (1998). The F-square statistic indicates that all exogenous variables have a significant impact on the endogenous variable.

Table 6: Path Coefficients (Mean, T-Values)

Path Coefficient	Sample Mean	St. Dev.	T-Value
Value			
Information Stage	0.5804	0.0113	51.5190
Purchase Stage	0.1569	0.0192	8.0152
Transaction Stage	0.3944	0.0135	29.1195

Examining the reliability and the validity of the perceived channel value scale at all four levels of the construct with an independent data set confirms the robustness of the developed scale. The final scale now includes 22 items which measure the perceived channel value across all three stages in the purchase process (see Appendix E).

9 Conclusions

In this study, we extend the knowledge of perceived channel value by developing and testing a parsimonious and practical three-dimensional scale of this construct. The reliability and validity tests indicate that the 22-item CHAVAL scale and its three dimensions have sound and stable psychometric properties. The scale demonstrates that customers assess channels not just by trading off quality versus price, but also consider factors such as the convenience and risk connected with a channel. Additionally, the scale has shown that distinct aspects are important across the different stages in the purchase process. Thus increasing the perceived channel value requires different strategies depending on the relevant stage in the purchase process. Recognition of the importance of the different components of perceived channel value across the different stages in the purchase process enables marketers to develop more sophisticated channel management and marketing strategies to increase a firm’s channel value.

The value of channels offered by a firm is a major asset in its battle for increased customer loyalty and the associated higher profits. Successful firms deliver value to customers by their commitment to the products and services sold as well as their distribution strategy.

The extent to which our findings may be extended to other channels remains to be explored. We employed customer reactions only for a selection of channels. However, we strongly believe that the scale is also appropriate for other channels as the items are formulated without any reference to channel-specific attributes.

We contribute to the literature by developing a scale measuring the channel value perceived by customers. This offers the opportunity to understand what determines the value of distribution channels and hence to improve the effectiveness and efficiency of multi-channel management.

10 References

Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentive to Participate in Electronic Marketplaces. *Journal of Marketing*, 61, 38-53.

Anderson, J. C., Jain, D. C., & Chintagunta, P. K. (1993). Customer Value Assessment in Business Markets: A State-of-Practice Study. *Journal of Business to Business Marketing*, 1, 3-30.

Babin, L. A., & Burns, A. C. (1998). A Modified Scale for the Measurement of Communication-Evoked Mental Imagery. *Psychology and Marketing*, 15, 261-278.

Bagozzi, R. P., & Baumgartner, H. (1994). The Evaluation of Structural Equation Models and Hypothesis Testing. In R. P. Bagozzi (Ed.), *Principles of Marketing Research* (pp. 386-422). Cambridge: Blackwell Publishers.

Bagozzi, R. P., & Phillips, L. W. (1982). Representing and Testing Organizational Theories: A Holistic Construal. *Administrative Science Quarterly*, 27, 459-489.

Bagozzi, R. P., & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Science*, 16, 74-94.

Bagozzi, R. P., Yi, Y., & Phillips, L. (1991). Assessing Construct Validity in Organizational Research. *Administrative Science Quarterly*, 36, 421-458.

Balasubramanian, S. (1998). Mail Versus Mall: A Strategic Analysis of Competition Between Direct Marketers and Conventional Retailers. *Marketing Science*, 17, 181-195.

Balasubramanian, S., Raghunathan, R., & Mahajan, V. (2005). Consumers in a Multichannel Environment: Product Utility, Process Utility, And Channel Choice. *Journal of Interactive Marketing*, 19, 12-30.

Bearden, W. O., Netemeyer, R. G., & Teel, J. E. (1989). Measurement of Consumer Susceptibility to Interpersonal Influence. *Journal of Consumer Research*, 15, 473-481.

Bishop, W. R. (1984). Competitive Intelligence. *Progressive Grocer*, 19-20.

Black, N. J., Lockett, A., Ennew, C., Winklhofer, H., & McKechnie, S. (2002). Modelling Consumer Choice Of Distribution Channels: An Illustration from Financial Services. *International Journal of Bank Marketing*, 20, 161-173.

Bohrnstedt, G. W. (1970). Reliability and Validity Assessment in Attitude Measurement. In G. F. Summers (Ed.), *Attitude Measurement* (pp. 80-99). London: Kershaw Publishing Company Limited.

Bolton, R. N., & Drew, J. H. (1991). A Multistage Model of Customers' Assessment of Service Quality and Value. *Journal of Consumer Research*, 17, 375-384.

Carmines, E. G., & Zeller, R. A. (1979). *Reliability and Validity Assessment*. Newbury Park: Sage Publications.

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and Utalitarian Motives for Online Retail Shopping Behavior. *Journal of Retailing*, 77, 511-535.

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. Hillsdale: Lawrence Erlbaum Associates.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic-Mail Emotion/Adoption Study. *Information Systems Research*, 14, 189-217.

Churchill, G. A. (1979). A Paradigm for Developing Better Measures of Marketing Constructs. *Journal of Marketing Research*, 16, 64-73.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale: Lawrence Erlbaum.

Cunningham, S. M. (1967). The Major Dimensions of Perceived Risk. In D. F. Cox (Ed.), *Risk Taking and Information Handling in Consumer Behavior* (pp. 82-108). Boston: Harvard University Press.

Dabholkar, P. A., Thorpe, D. I., & Rentz, J. O. (1996). A Measure of Service Quality for Retail Stores: Scale Development and Validation. *Journal of the Academy of Marketing Science*, 24, 3-16.

Devlin, J. F. (2002). Customer Knowledge and Choice Criteria in Retail Banking. *Journal of Strategic Marketing*, 10, 273-290.

Devlin, J. F., & Yeung, F. T. (2003). Insights into Customer Motivations for Switching to Internet Banking. *International Review of Retail, Distribution and Consumer Research*, 13, 375-392.

Dholakia, R. R., & Uusitalo, O. (2002). Switching to Electronic Stores: Consumer Characteristics and the Perception of Shopping Benefits. *International Journal of Retail & Distribution Management*, 30, 459-469.

Diamantopoulos, A., & Winklhofer, H. (2001). Index Construction with Formative Indicators: An Alternative to Scale Development. *Journal of Marketing Research*, 38, 269-277.

Doyle, M. (1984). New Ways of Measuring Value. *Progressive Grocer*, 15-19.

Fader, P. S., Hardie, B., & Lee, K. L. (2003). *"Counting Your Customers" The Easy Way: An Alternative to the Pareto/NBD Model*. Working Paper, Wharton School, Philadelphia.

Fink, A. (2003). *Asking Survey Questions*. Thousand Oaks: Sage Publication.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18, 39-50.

Forsythe, S., Liu, C., Shannon, D., & Gardner, L. C. (2006). Development of a Scale to Measure the Perceived Benefits and Risks of Online Shopping. *Journal of Interactive Marketing*, 20, 55-75.

Gerbing, D. W., & Anderson, J. C. (1988). An Updated Paradigm for Scale Development Incorporating Unidimensionality and Its Assessment. *Journal of Marketing Research*, 25, 186-192.

Geyskens, I., Gielens, K., & Dekimpe, M. G. (2002). The Marketing Valuation of Internet Channel Addition. *Journal of Marketing*, 66, 102-119.

Gradial, S., Clemons, S. D., Woodruff, R. B., Schumann, D. W., & Burns, M. J. (1994). Comparing Consumers' Recall of Prepurchase and Postpurchase Evaluation Experiences. *Journal of Consumer Research*, 20, 548-560.

Grewal, D., Levy, M., & Marshall, G. W. (2002). Personal Selling in Retail Settings: How Does the Internet and Related Technologies Enable and Limit Successful Selling? *Journal of Marketing Management*, 18, 301-316.

Gupta, A., Su, B.-C., & Walter, Z. (2004). An Empirical Study of Consumer Switching from Traditional to Electronic Channels: A Purchase-Decision Perspective. *International Journal of Electronic Commerce*, 8, 131-161.

Hair, J. F., Black, B., Babin, B., Anderson, R. E., & Tatham, R. L. (2005). *Multivariate Data Analysis*. Upper Saddle River: Prentice Hall.

Hansen, G. (1987). Forecasting Error and Multicollinearity. In, *Jahrbuch für Nationalökonomie und Statistik* (pp. 517-531). Stuttgart: G. Fischer Verlag.

Hauser, R. M., & Goldberger, A. S. (1971). The Treatment of Unobservable Variables in Path Analysis. In H. L. Costner (Ed.), *Sociological Methodology* (pp. 81-117). San Francisco: Jossey-Bass.

Hitt, L. M., & Frei, F. X. (2002). Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking. *Management Science*, 48, 732-748.

Holbrook, M. B., & Corfman, K. P. (1985). Quality and Value in the Consumption Experience: Phaedrus Rides Again. In J. Jacoby, & J. Olson (Eds.), *Perceived Quality* (pp. Lexington: Lexington Books.

Hulland, J. (1999). Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies. *Strategic Management Journal*, 20, 195-204.

Kaufman-Scarborough, C., & Lindquist, J. D. (2002). E-Shopping in a Multiple Channel Environment. *Journal of Consumer Marketing*, 19, 333-350.

Keeney, R. (1999). The Value of Internet Commerce to the Customer. *Management Science*, 45, 533-542.

Lattin, J. M., Carroll, D. J., & Green, P. E. (2003). *Analyzing Multivariate Data*. Pacific Grove: Thomson Learning.

Lee, K. S., & Tan, S. J. (2003). E-Retailing versus Physical Retailing: A Theoretical Model and Empirical Test of Consumer Choice. *Journal of Business Research*, 56, 877-885.

Levy, M. (1999). Revolutionizing the Retail Pricing Game. *Discount Store News*, 38, 15.

Lohmöller, J.-B. (1989). *Latent Variable Path Modeling with Partial Least Squares*. Heidelberg: Physica-Verlag.

Mathieson, K., Peacock, E., & Chin, W. W. (1996). *Extending the Technology Acceptance Model: The Influence of Perceived User Resources*. White Paper, Calgary: University of Calgary.

May, E. G., & Greyser, S. A. (1989). From Home-Shopping: Where Is It Leading? In L. Pellegrini, & S. K. Reddy (Eds.), *Retail and Marketing Channels - Economic and Marketing Perspectives on Producer-Distributor Relationships* (pp. 216-233). London: Routledge.

Monroe, K. B. (1990). *Pricing: Making Profitable Decisions*. New York: McGraw-Hill.

Montoya-Weiss, M. M., Voss, G. V., & Grewal, D. (2003). Determinants of Online Channel Use and Overall Satisfaction with a Relational, Multichannel Service Provider. *Journal of the Academy of Marketing Science*, 31, 448-458.

Oliver, R. L. (1997). *Satisfaction: A Behavioral Perspective on the Consumer*. New York: McGraw-Hill.

Parasuraman, A., & Grewal, D. (2000). The Impact of Technology on the Quality-Value-Loyalty Chain: A Research Agenda. *Journal of the Academy of Marketing Science*, 28, 168-174.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A Conceptual Model of Service Quality and Its Implications for Future Research. *Journal of Marketing*, 49, 41-50.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing*, 64, 12-40.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of Expectations as a Comparison Standard in Measuring Service Quality: Implications for Future Research. *Journal of Marketing*, 58, 111-124.

Peter, P. J. (1979). Reliability: A Review of Psychometric Basics and Recent Marketing Practices. *Journal of Marketing Research*, 16, 6-17.

Peter, P. J. (1981). Construct Validity: A Review of Basic Issues and Marketing Practices. *Journal of Marketing Research*, 18, 133-145.

Rangaswamy, A., & Van Bruggen, G. H. (2005). Opportunities and Challenges in Multichannel Marketing: An Introduction to the Special Issue. *Journal of Interactive Marketing*, 19, 5-11.

Reardon, J., & McCorkle, D. (2002). A Consumer Model for Channel Switching Behaviour. *International Journal of Retail & Distribution Management*, 30, 179-185.

Reinartz, W. J., Krafft, M., & Hoyer, W. D. (2004). The CRM Process: Its Measurement and Impact on Performance. *Journal of Marketing Research*, 41, 1-33.

Rossiter, J. R. (2002). The C-OAR-SE Procedure for Scale Development in Marketing. *International Journal of Research in Marketing*, 19, 305-335.

Rugimbana, R., & Iversen, P. (1994). Perceived Attributes of ATMs and their Marketing Applications. *International Journal of Bank Marketing*, 12, 30-35.

Schoenbachler, D. D., & Goeffrey, G. L. (2002). Multi-Channel Shopping: Understanding What Drives Channel Choice. *Journal of Consumer Marketing*, 19, 42-53.

Selltiz, C., Wrightsman, L. S., & Cook, S. W. (1976). *Research Methods in Social Relations*. New York: Holt, Rinehart, and Winston.

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why We Buy What We Buy: A Theory of Consumption Values. *Journal of Business Research*, 22, 159-170.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer Loyalty in E-Commerce: An Exploration of its Antecedents and Consequences. *Journal of Retailing*, 78, 41-50.

Sweeney, J. C., & Soutar, G. N. (2001). Consumer Perceived Value: The development of a multiple item scale. *Journal of Retailing*, 77, 203-220.

Sweeney, J. C., Soutar, G. N., & Johnson, L. W. (1999). The Role of Perceived Risk in the Quality-Value Relationship: A Study in a Retail Environment. *Journal of Retailing*, 75, 77-105.

Thomas, J. S., & Sullivan, U. Y. (2005). Managing Marketing Communications with Multichannel Customers. *Journal of Marketing*, 69, 239-251.

Tse, A. C. B., & Yim, F. (2001). Factors Affecting The Choice of Channels: Online vs Conventional. *Journal of International Consumer Marketing*, 14, 137-153.

Wallace, D. W., Giese, J. L., & Johnson, J. L. (2004). Customer Retailer Loyalty in the Context of Multiple Channel Strategies. *Journal of Retailing*, 80, 249-263.

Williamson, O. E. (1985). *The Economic Institutions of Capitalism*. New York: Free Press.

Woodruff, R. B. (1997). Customer Value: The Next Source for Competitive Advantage. *Journal of the Academy of Marketing Science*, 25, 139-153.

Zaichowsky, J. L. (1985). Measuring the Involvement Construct. *Journal of Consumer Research*, 12, 341-352.

Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing*, 52, 2-22.

Zeithaml, V. A., & Gilly, M. C. (1987). Characteristics Affecting the Acceptance of Retailing Technologies: A Comparison of Elderly and Nonelderly Consumers. *Journal of Retailing*, 63, 49-68.

Appendix A: Exploratory Investigation of Dimensionality – First Data Set – Purchase Stage

Item	Quality	Risk	Conv.*	Price
This channel offers an individualized service when purchasing a product.	0.5117			
The products offered on this channel satisfy all my needs.	0.7561			
The products offered on this channel increase my trust.	0.6568			
The service quality when purchasing on this channel is constantly good.	0.6126			
Problems arising when using this channel are resolved quickly.	0.6844			
This channel offers a good service when I need it.	0.7158			
I perceive the channel not to be suited to purchasing products.	0.5177			
The service offered on this channel meets my expectations.	0.5062			
The products offered meet my expectations.	0.5313			
The products offered on this channel are exactly what I am looking for.	0.6310			
Product purchases through this channel are always performed in time.	0.5624			
Purchasing products through this channel involves low risk.		0.6247		
Purchasing products on this channel involves higher risk compared to others.		-0.7818		
When using this channel I am worried this will not be advantageous.		-0.7229		
I feel safe when purchasing products through this channel.		0.6830		
I am not worried that I will be involved in something risky when using this…		0.5182		
Error free purchase is guaranteed on this channel,		0.5963		
On this channel the likelihood of a wrong purchase is especially high.		-0.7946		
On this channel I am especially likely to get a product purchase wrong.		-0.7385		
This channel offers a low quality service.		-0.6511		
The channel design facilitates the purchase of products.			0.6866	
It is easy to purchase products on this channel.			0.7662	
Purchasing products on this channel requires little effort.			0.9084	
This channel offers me a lot of convenience when purchasing products.			0.7398	
Purchasing products on this channel is very inconvenient.			-0.7776	
Purchasing products on this channel is very troublesome.			-0.8179	
This channel allows me to purchase products with convenience.			0.7304	
This channel allows me to purchase products at any time			0.8034	
I need a lot of time purchasing products on this channel.			-0.7543	
I am flexible about when I purchase products through this channel.			0.8268	
I need only little time to purchase products on this channel.			0.6977	
The price-performance ratio offered is better than on other channels.				0.6603
I might purchase products at an inflated price on this channel.				0.7706
The prices offered on this channel are lower than on other channels.				0.6121
The prices offered on this channel are higher than on other channels.				0.7912
The interest offered on investment products is low on this channel.				0.5873
The interest for loan products is high on this channel.				0.5952
Investment products purchased on this channel carry high interest.				0.8027
Loan products purchased on this channel carry low interest.				0.7374
The prices paid when using this channel are justified.				
The opportunities for product purchase offered on this channel are sufficient.				

Note: All loadings below 0.5 have been suppressed; Conv. = Convenience

Appendix B: Exploratory Investigation of Dimensionality – First Data Set – Transaction Stage

Item	Conv.*	Risk	Price
The service offered by this channel satisfies all my needs.	0.5310		
The channel design eases the execution of transactions.	0.8716		
It is easy to conduct transactions on this channel.	0.8847		
Conducting transactions on this channel requires little effort.	0.8358		
Conducting transactions on this channel is very inconvenient.	-0.7517		
This channel allows me to conduct transactions with convenience.	0.8150		
I am flexible about when I conduct transactions through this channel.	0.8586		
I need only a little time to conduct transactions on this channel.	0.8163		
I perceive the channel not to be suited to conducting transactions.	0.6380		
The service offered on this channel meets my expectations.	0.6626		
The opportunities to execute transactions meet my expectations.	0.5568		
Conducting transactions through this channel involves low risk.		0.5794	
Conducting transactions on this channel involves higher risk compared to others.		-0.7365	
When using this channel I am worried this will not be advantageous.		-0.7231	
I feel safe when conducting transactions through this channel.		0.8359	
I am not worried that I will be involved in something risky when using this channel.		0.5368	
The service offered by this channel increases my trust.		0.6149	
Error free transaction execution is guaranteed on this channel.		0.7092	
On this channel the likelihood of incorrect transactions execution is especially high.		-0.6920	
I perceive the quality of the service offered by this channel to be constantly good.		0.5214	
Using this channel transactions are especially likely to be executed wrongly.		-0.6499	
This channel offers a low quality service.		-0.6143	
The prices offered on this channel are lower than on other channels.			-0.8132
The prices offered on this channel are higher than on other channels.			0.8614
The fees for using this channel are higher than on other channels.			0.8005
The fees demanded for using this channel are justified.			0.8828
The terms for using this channel are justified.			0.8105
The prices paid when using this channel are justified.			0.8797
The transaction portfolio offered on this channel is exactly what I am looking for.	0.5192	0.5382	
The service offered by this channel is sufficient.			
On this channel I receive individualized service when conducting transactions.			
This channel offers me a lot of convenience when conducting transactions.			
Conducting transactions on this channel is very troublesome.			
This channel allows me to conduct transactions at any time.			
I need a lot of time to conduct transactions on this channel.			
Problems arising while using this channel are resolved quickly.			
This channel offers a good service when I need it.			
Transactions through this channel are always executed on time.			

Note: All loadings below 0.5 have been suppressed; Conv. = Convenience

Appendix C: Results of Confirmatory Factor Analysis – First Data Set – Purchase Stage

Item	Loading	Indicator Reliability	T-Value
Quality			
Product purchases through this channel are always performed in time.	-0.0874	0.0076	10.0882
This channel offers an individualized service when purchasing a…	0.5236	0.2741	5.1193
The products offered on this channel satisfy all my needs.	0.7611	0.5792	12.3138
The products offered on this channel increase my trust.	0.7394	0.5467	11.0594
Problems arising when using this channel are resolved quickly.	0.7732	0.5978	12.9024
This channel offers a good service when I need it.	0.7262	0.5274	11.5161
I perceive the channel not to be suited to purchasing products.	0.7082	0.5016	13.8367
The service offered on this channel meets my expectations.	0.7547	0.5696	23.0026
The products offered meet my expectations.	0.7775	0.6045	16.4503
The products offered on this channel are exactly what I am looking…	0.7460	0.5565	20.3881
The service quality when purchasing on this channel is constantly…	0.7500	0.5626	16.1348
Convenience			
The channel design facilitates the purchase of products.	0.7489	0.5609	17.5481
I am flexible about when I purchase products through this channel.	0.8028	0.6445	14.8885
I need only a little time to purchase products on this channel.	0.7057	0.4981	11.9065
It is easy to purchase products on this channel.	0.7983	0.6373	33.8469
Purchasing products on this channel requires little effort.	0.9027	0.8149	41.5943
This channel offers me a lot of convenience when purchasing…	0.7723	0.5964	25.2514
Purchasing products on this channel is very inconvenient.	-0.7083	0.5017	9.7927
Purchasing products on this channel is very troublesome.	-0.7991	0.6386	18.3391
This channel allows me to purchase products with convenience.	0.7829	0.6129	19.5917
This channel allows me to purchase products at any time.	0.7800	0.6084	12.8606
I need a lot of time purchasing products on this channel.	-0.7137	0.5093	10.0882
Risk			
On this channel I am especially likely to get a product purchase…	-0.7587	0.5756	1.0121
This channel offers a low quality service.	-0.7294	0.5321	1.0037
Error free purchase is guaranteed on this channel.	0.7643	0.5842	1.0108
On this channel the likelihood of a wrong purchase is especially high.	-0.7621	0.5808	1.0152
Purchasing products through this channel involves low risk.	0.6766	0.4578	1.3624
Purchasing products on this channel involves higher risk compared…	-0.7477	0.5591	1.3052
When using this channel I am worried this will not be advantageous.	-0.6814	0.4643	1.2739
I feel safe when purchasing products through this channel.	0.7978	0.6365	1.3613
I am not worried that I will be involved in something risky when…	0.5848	0.3420	1.3697
Price			
The price-performance ratio offered is better than on other channels.	0.7664	0.5873	1.0419
I might purchase products at an inflated price on this channel.	0.7286	0.5308	1.2364
The prices offered on this channel are lower than on other channels.	0.7533	0.5675	1.1387
The prices offered on this channel are higher than on other channels.	0.7927	0.6283	1.2443
The interest offered on investment products is low on this channel.	0.6739	0.4541	1.2592
The interest for loan products is high on this channel.	0.6363	0.4049	1.2889
Investment products purchased on this channel carry high interest.	0.7449	0.5549	1.3778
Loan products purchased on this channel carry low interest.	0.6463	0.4177	0.3043

Appendix D: Results of Confirmatory Factor Analysis – First Data Set – Transaction Stage

Item	Loading	Indicator Reliability	T-Value
Convenience			
It is easy to conduct transactions on this channel.	0.8550	0.7311	30.8412
The channel design eases the execution of transactions.	0.8719	0.7602	36.9597
I am flexible about when I conduct transactions through this channel.	0.8160	0.6658	25.9606
Conducting transactions on this channel requires little effort.	0.8041	0.6466	23.0951
I need only a little time to conduct transactions on this channel.	0.7820	0.6115	21.7900
This channel allows me to conduct transactions with convenience.	0.7905	0.6248	29.4444
The service offered on this channel meets my expectations.	0.7689	0.5913	16.0134
I perceive the channel not to be suited to conducting transactions.	0.7298	0.5326	13.8880
The opportunities to execute transactions meet my expectations.	0.6788	0.4608	10.6240
The service offered by this channel satisfies all my needs.	0.6069	0.3684	7.7229
Conducting transactions on this channel is very inconvenient.	-0.7373	0.5436	14.2012
Risk			
When using this channel I am worried this will not be advantageous.	-0.7186	0.5163	3.7432
I am not worried that I will be involved in something risky when…	0.6035	0.3642	4.5105
Conducting transactions through this channel involves low risk.	0.5789	0.3351	3.9101
The service offered by this channel increases my trust.	0.6390	0.4083	5.2508
On this channel the likelihood of incorrect transaction execution is…	-0.6457	0.4169	2.7947
Using this channel transactions are especially likely to be executed…	-0.6972	0.4861	4.3013
This channel offers a low quality service.	-0.6136	0.3765	5.5713
I feel safe when conducting transactions through this channel.	0.8233	0.6778	4.2905
Error free transaction execution is guaranteed on this channel.	0.6994	0.4892	4.4271
I perceive the quality of the service offered by this channel to be…	0.5595	0.3130	6.1186
Conducting transactions on this channel involves higher risk…	-0.6708	0.4500	2.6042
Price			
The fees demanded for using this channel are justified.	0.8616	0.7423	3.1149
The prices paid when using this channel are justified.	0.7488	0.5607	3.4792
The terms for using this channel are justified.	0.6648	0.4420	3.4395
The prices offered on this channel are higher than on other channels.	0.7542	0.5688	3.3209
The fees for using this channel are higher than on other channels.	0.7930	0.6288	3.4020
The prices offered on this channel are lower than on other channels.	0.6718	0.4514	3.3804

Appendix E: CHAVAL Scale

Item
Information
Quality
The information offered on this channel satisfies all my needs.
The information offered meets my expectations.
On this channel I receive individualized information.
Convenience
The channel design eases the search for information.
This channel offers me a lot of convenience when seeking information.
Risk
I feel safe when seeking information using this channel.
Information search on this channel involves higher risk compared to others.
Purchase
Quality
The products offered meet my expectations.
The products offered on this channel are exactly what I am looking for.
The products offered on this channel satisfy all my needs.
Convenience
Purchasing products on this channel requires little effort.
I am flexible about when I purchase products through this channel.
Risk
On this channel the likelihood a wrong purchase is especially high.
On this channel I am especially likely to get a product purchase wrong.
Price
I might purchase products at an inflated price on this channel.
The prices offered on this channel are higher than on other channels.
Transaction
Convenience
The channel design eases the execution of transactions.
It is easy to conduct transactions on this channel.
I need only a little time to conduct transactions on this channel.
Risk
I feel safe when conducting transactions through this channel.
Price
The prices offered on this channel are higher than on other channels.
The fees for using this channel are higher than on other channels.

Beitrag 5

Evaluating Customer Channel Migration Activities

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Eingereicht zum

International Journal of Research in Marketing

Juli 2006

Evaluating Customer Channel Migration Activities

Abstract

Firms increasingly intend to migrate customers to their non-store distribution channels such as the internet with the aim of reducing costs of distribution. But customer migration is only advisable as long as the potential cost reductions exceed the necessary investments for migration measures. In order to make a sound decision on whether or not to implement certain migration measures, it is therefore fundamental to determine their potential cost reductions and necessary investments.

Hence, the aim of this paper is to model customer channel usage behavior across the different stages of the purchase process in order to make predictions about the impact of channel migration measures on individual channel usage behavior and on potential cost reductions. This allows to make decisions of whether or not to implement channel migration measures.

Keywords: Channel Choice, Latent Class Analysis, Financial Services Industry

1 Introduction

The past decade has seen rapid and substantive changes in channels of distribution for goods as well as for services. Firms have increasingly implemented non-store distribution channels such as the internet in hope of reducing costs of distribution (Prasad & Harker 2000; Anderson & Lanen 2002; Hitt & Frei 2002; Hoffman 2002).

The hope of reducing costs by introducing non-store distribution channels stems from the opportunity to centralize and to externalize labor intensive processes (Myers, Pickersgill, & Van Metre 2004). Many customer interactions are still performed by a decentralized store network. Using a centralized infrastructure instead such as the internet or the call center allows for a more efficient use of a firm's resources and for a higher degree of automation (Kumar & Venkatesan 2005). In addition, non-store distribution channels are designed to increase the degree of self-servicing by the customer. More transactions are performed by the customer herself without any need for an employee of the firm to interact with the customer. Both these changes are assumed to lead to a reduction in costs in customer interactions (Ansari, Mela, & Neslin 2005).

Nevertheless, too often firms are adding non-store distribution channels only to see rising costs of distribution (Myers, Pickersgill, & Van Metre 2004; Van Baal & Dach 2005). The proliferation of non-store distribution channels presents customers with a real choice in terms of channel (Black et al. 2002). As a consequence, customers choose the channel which best meets their needs (Rangaswamy & Van Bruggen 2005). But the preferred channel from a customer's perspective might not always coincide with the channel being the most economic from a firm's perspective (Myers, Pickersgill, & Van Metre 2004). The customer's free choice of channels combined with the incremental infrastructure cost of an additional channel still out-weight the cost reductions which are realized by transferring transactions from a high to a low cost channel (Hitt, Frei, & Harker 1999).

Only by actively managing a customer's channel usage behavior it is possible to capture the cost reduction potential offered by non-store distribution channels (Myers, Pickersgill, & Van Metre 2004). Firms must begin to manage their customers' channel usage behavior in order to quickly recoup their investments in non-store distribution channels.

However, customer channel migration is not on easy task as it has to balance the economics of a migration measure and a customer's channel preferences (Ansari, Mela, & Neslin 2005). For instance, firms can not simply abolish the store channel with the intention to reduce costs, because customers might defect if firms discontinued this channel (Myers, duce costs, because customers might defect if firms discontinued this channel (Myers, Pickersgill, & Van Metre 2004). Instead, effective channel migration measures should intend to realize a positive profit contribution by altering a customer's channel perception and hence channel usage behavior.

In order to make a sound decision on whether or not to implement certain migration measures, it is fundamental to determine their potential cost reductions and necessary investments. Estimating the potential cost reductions of customer migration requires to make predictions about the impact of channel migration measures on a customer's channel usage behavior. Predicting channel usage behavior on the other hand necessitates a deep understanding of how customers build channel preferences and choose between different channels (Black et al. 2002). It requires to identify the relevant influencing factors and their impact on the channel choice decision depending on whether the customer intends to search for information, to purchase a product, or to use a previously purchased product (Thomas & Sullivan 2005). For instance, a customer might prefer a remote channel such as the internet when seeking information. When making a purchase the same customer might prefer going to the store. Finally, when using the product the customer might wish to interact with the firm through a call center (Moon 2004). A lack of understanding will inhibit the prediction of changes in a customer's channel usage behavior and the respective cost reductions due to customer channel migration.

The aim of this paper is to model customer channel choice behavior across the different stages of the purchase process in order to make predictions about the impact of channel migration measures on individual channel usage behavior and on the resulting cost reductions.

The remainder of the paper is organized as follows. In the next section, the relevant literature is reviewed on how to model a customer's channel choice behavior. Then we describe how to model channel choice which is followed by a section describing the data collection and measurement. The empirical results are then discussed in detail in the following section. Afterwards, the methodology to predict the impact of customer migration on channel usage and on the potential cost reductions as well as the respective results are presented. The conclusions and managerial implications are formulated in the final section.

2 Literature Review

In the literature review we will first highlight the lack of research investigating a customer's channel choice behavior in a multi-channel environment and across multiple stages of the purchase process. We then will review the relevant literature to identify the factors influencing a customer's channel choice.

2.1 Channel Choice Research

The literature review reveals no research which models a customer's channel choice in a multi-channel environment across multiple stages of the purchase process. Table 1 summarizes the prior research.

Table 1 Literature on Channel Choice

	Number of Channels	
Number of purchase process stages	**Single (Channel Adoption)**	**Multiple (Channel Choice)**
One	e.g. - Gupta, Su, & Walter 2004 - Inman, Shankar, & Ferraro 2004 - Kacen, Hess, & Chiang 2005 - Pikkarainen et al. 2004 - Teo, Leong, & Wang 2004	- Strebel, Erdem, & Swait 2004 - Thomas & Sullivan 2005
Multiple	- Montoya-Weiss, Voss, & Grewal 2003 - Moon 2004 - Ramaswami, Strader, & Brett 2001 - Sorce, Perotti, & Widrick 2005	- THIS PAPER

Some studies investigate the adoption of only a single channel for one specific stage of the purchase process (e.g. Gupta, Su, & Walter 2004; Inman, Shankar, & Ferraro 2004). This stream of research was initiated by the emergence of new technologies such as the call center and the internet. Researchers started to investigate why customers adopt a certain channel or not (Black et al. 2002). The aim of the adoption literature is therefore to identify the factors which foster or hinder the adoption of a new channel with the aim to model a channel's acceptance among customers. For example, Pikkarainen et al. (2004) investigate the online banking acceptance in the light of the traditional technology acceptance model.

As the range of distribution channels available to customers increased, customers had a real choice in terms of channel. Inspired by these new opportunities, an increasing number of customers started using multiple channels (Kumar & Venkatesan 2005). Hence, it became increasingly important to understand the factors that lead customers to choose one channel over the other (Balasubramanian 1998). As a consequence, the channel adoption literature was extended towards the context of a multi-channel environment and focused on the modeling of channel choice (Strebel, Erdem, & Swait 2004; Thomas & Sullivan 2005). Nevertheless, this research neglects the fact that a customer's channel preference depends as well on the stage of the purchase process (Balasubramanian, Raghunathan, & Mahajan 2005; Van Baal & Dach 2005). Some customers may choose one channel across all stages of the purchase process. Others may rely on different channels at different stages of the purchase process (Balasubramanian, Raghunathan, & Mahajan 2005). This channel switching behavior is described in several studies and supports the hypothesis that the likelihood to choose a certain channel depends on the stage of the purchase process (Rasch & Lintner 2001; Ward & Morganosky 2002).

Only the channel adoption literature has already been extended to account for multiple stages of the purchase process (Ramaswami, Strader, & Brett 2001; Montoya-Weiss, Voss, & Grewal 2003; Moon 2004; Sorce, Perotti, & Widrick 2005). This stream of literature shows that the stage of the purchase process not only has an impact on a customer's willingness to adopt a channel but as well has an impact on the relevance of the factors influencing channel choice (Ramaswami, Strader, & Brett 2001).

The studies in Table 1 contribute significantly to the emerging area of channel choice. However, none has modeled the customer channel choice behavior in a multi-channel environment across the different stages of the purchase process in order to make predictions about the impact of channel migration measures on individual channel usage behavior and on the resulting cost reductions.

2.2 Literature on How to Model Channel Choice

The critical aspect of modeling channel usage is not choosing the model (e.g. Multinomial Logit or Probit Model) as much as it is specifying the model (Thomas & Sullivan 2005). Hence, it is important to identify the relevant factors that influence a customer's channel choice. A literature review generates a large number of channel choice factors which can be grouped in three categories: *channel specific factors*, *situation specific factors*, and *customer specific factors*.

Channel Specific Factors

The choice of a channel is primarily driven by its benefits and costs for the customer related to its use (Schoenbachler & Goeffrey 2002; Darian, Wiman, & Tucci 2005). In other words, the choice of a channel depends to a large degree on its attributes perceived by the customers (Gehrt & Yale 1996; Eastlick & Liu 1997; Forsythe et al. 2006).

By reviewing the existing literature four channel attributes can be elicited which influence channel choice (see Appendix A):

- perceived service quality provided by the channel (Tse & Yim 2001; Montoya-Weiss, Voss, & Grewal 2003),
- perceived convenience offered by the channel (Keeney 1999; Tse & Yim 2001; Black et al. 2002; Dholakia & Uusitalo 2002; Grewal, Levy, & Marshall 2002; Reardon & McCorkle 2002; Srinivasan, Anderson, & Ponnavolu 2002; Devlin & Yeung 2003),
- perceived risk involved when using the channel (Black et al. 2002; Grewal, Levy, & Marshall 2002; Reardon & McCorkle 2002; Schoenbachler & Goeffrey 2002; Devlin & Yeung 2003; Montoya-Weiss, Voss, & Grewal 2003), and
- costs of conducting business through the channel (Tse & Yim 2001; Black et al. 2002; Devlin 2002; Grewal, Levy, & Marshall 2002; Reardon & McCorkle 2002; Fader, Hardie, & Lee 2005).

The perceived service quality of a channel is determined by the channel's ability to satisfy the needs and to fulfill the expectations of the customers (Gronroos 1984; Parasuraman, Zeithaml, & Berry 1988). Perceived convenience refers to the extent to which a customer feels that a channel is easy to access and use (Durkin et al. 2003). Following Stone & Gronhaug 's (1993) conceptualization, perceived risk is defined as the subjective expectation of a loss. While a number of risk dimensions have been suggested, only two are relevant to assess the perceived risk of a channel (Cunningham 1967): financial and performance risk. The perceived costs of conducting business through a channel can be defined as the monetary sacrifice a customer has to make or the price she has to pay when using a specific channel (Zeithaml 1988).

Situation Specific Factors

The store choice literature argues that the perceived value of a store depends not only on a store's attributes but as well on situation specific factors (e.g. Mattson 1982). Hence, the importance of a store attribute for the choice decision might vary across different usage situations.

Similarly as in the store choice literature situational variables have an effect on channel choice (Morrison & Roberts 1998; Balasubramanian, Raghunathan, & Mahajan 2005; Van Baal & Dach 2005). Two situational variables which are hypothesized to have an impact on channel choice are the product being considered and the stage of the purchase process.

Morrison & Roberts (1998) show a strong correlation between product and channel use. They demonstrate that the product being considered influences the preference for a channel and therefore has an impact on channel choice.

Balasubramanian, Raghunathan, & Mahajan (2005) and Van Baal & Dach (2005) argue that the choice of a channel depends as well on the stage of the purchase process. For instance, a customer might use the internet to seek information about a product, then purchases the product in a store, and finally uses the product by engaging with the call center. This channel switching behavior is explained by the changing preference structure when going through the purchase process (Rasch & Lintner 2001; Ward & Morganosky 2002). In other words, the importance of channel attributes on a customer's channel choice decision might vary across the different stages of the purchase process (Boehm & Gensler 2006).

Customer Specific Factors

Furthermore, the choice of a channel depends as well on the customer herself. As a consequence, channel choice across customers can be different even though the characteristics of the situation and the available channels are the same (Keeney 1999). The early literature focused therefore on the demographic differences between users and non-users of a specific channel. Past research showed that demographic variables might be associated with channel patronage (Crask & Reynolds 1978; Korgaonkar, Lund, & Price 1985). Nevertheless, conflicting findings have been reported (e.g. Darian 1987; Gehrt, Ingram, & Howe 1988). While some studies report that for instance in-home shoppers are more affluent, and well educated (Darian 1987; Balabanis & Vassileiou 1999), other studies come to opposing conclusions (Peters & Ford 1972; Akaah, Korgaonkar, & Lund 1995). Therefore it is not clear how customer characteristics affect channel choice.

The intrinsic channel preference is an additional customer specific variable hypothesized to influence channel choice (Black et al. 2002). The brand choice literature has already shown that customers differ in their preference for certain brands and in the importance they assign to the brand (e.g. Singh, Hansen, & Gupta 2005). A similar preference structure might exist for channel choice. Customers will most likely have an intrinsic preference for a certain channel and are therefore more receptive to choose this channel (Lee 2002; Montoya-Weiss, Voss, & Grewal 2003).

Finally, a customer's channel choice is influenced as well by the experience of a customer with a specific channel (Ward & Morganosky 2002). Customers who are familiar with a specific channel will be more likely to use this channel again compared to customers who have not been accustomed to use this channel.

3 Modeling Channel Choice

Customers choose the channel which provides the highest utility in a given situation (Alba et al. 1997). Channel choice can therefore be modeled based on the concept of utility maximization using a Multinomial Logit or Probit Model (Lee & Tan 2003). We use a Multinomial Logit Model (MNL) to model a customer's channel choice.

The MNL model allows to include the channel attributes as identified in the literature review – quality, convenience, risk, and cost – as independent variables. At the same time, it takes situation specific variables into account such as the product being considered (McFadden 1974). The second situation specific variable, the stage of the purchase process is hypothesized to have a fundamental impact on a customer's preference structure and hence on channel choice. Thus, it can be best considered by estimating separate models for each stage of the purchase process.

Finally, the MNL model accommodates for customer specific variables. We account for a customer's channel experience by including the channel used in the previous stage of the purchase process (between-stage experience) and the channel used in a previous usage situation (within-stage experience). These variables capture the effect of previous channel use on the current channel choice and therefore represent the effect of channel experience or inertia. Including a variable representing the channel use in the previous stage of the purchase process furthermore accounts for the interrelation between the different stages of the purchase process.

As dependent variable we use the channel usage intention measured by a constant sum scale rather than the actual channel use measured by a dummy variable due to two reasons: first, to receive reliable estimates, it is essential that the time when observing the choice of a channel coincides with the measurement of the independent variables (Kumar, Aaker, & Day 2002, p.126). Due to a long interpurchase time in certain industries, this requirement might be violated. Using the channel usage intention as the dependent variable overcomes this problem as it allows to survey the dependent and independent variables at the same point in time. Second, customers often use a mix of channels at each stage of the purchase process to interact with the firm. For instance, customers might use the store and the internet simultaneously to seek information about a product. Yet again they might use a different mix of channels in the purchase or transaction stage of the purchase process. In order to account for the use of such a channel mix customers are asked in a questionnaire to attach a choice probability to each available alternative rather than choosing only one alternative out of a set of channels (Van den Poel & Leunis 1999).

Since customers differ in their preferences for channel attributes and their intrinsic channel preference, unobserved heterogeneity has to be taken into account when modeling customer channel choice. We therefore estimate a latent class MNL model (Kamakura & Russell 1989). The probabilities of channel choice are modeled as follows:

$$P\left(y_i = m \middle| s, z_i^{lag}, z_i^{att}\right) = \frac{\exp\left(\beta_{s,m}^{cons} + \beta_{s,m}^{lag} \cdot z_{i,r}^{lag} + \sum_{p \in P} \beta_{s,p}^{att} \cdot z_{i,r,m,p}^{att}\right)}{\sum_{m' \in M} \exp\left(\beta_{s,m'}^{cons} + \beta_{s,m'}^{lag} \cdot z_{i,r}^{lag} + \sum_{p \in P} \beta_{s,p}^{att} \cdot z_{i,r,m',p}^{att}\right)} \quad \forall i \in I \tag{1}$$

$P\left(y_{i,r} = m\right)$:	probability of customer i considering product r to choose channel m,
$y_{i,r}$:	dependent variable indicating the channel customer i considering product r intends to choose,
$\beta_{s,m}^{cons}$:	coefficient of the intrinsic preference of latent class s for channel m,
$\beta_{s,m}^{lag}$:	coefficient of the channel m used at the previous stage of the purchase process for latent class s,
$z_{i,r}^{lag}$:	variable indicating channel m was used at the previous stage of the purchase process by customer i considering product r,
$\beta_{s,p}^{att}$:	coefficient of channel attribute p for latent class s,
$z_{i,r,m,p}^{att}$:	perception of channel attribute p of channel m for customer i considering product r.

Using replication weights accounts for the fact that the dependent variable is operationalized as a customer's usage intention of a mix of distribution channels (Vermunt & Magidson 2004). The probability density is formulated as follows:

$$P\left(y_i \middle| z_i\right) = \sum_{s=1}^{S} P(s) \prod_{r=1}^{R_i} \left[P\left(y_{i,r} \middle| s, z_{i,r}^{lag}, z_{i,r}^{att}\right)\right]^{v_{i,r}} \tag{2}$$

$v_{i,r}$: replication weight for customer i considering product r.

Finally, the latent class approach allows as well to test whether customer demographics have an impact on a customer's channel choice. Comparing the descriptive demographics of the estimated latent classes allows to determine whether significant differences exist. In the case that differences between the latent classes are present, it can be concluded that customer demographics have an impact on channel use.

4 Data Collection and Measurement

A questionnaire among 500 randomly selected German banking customers has been conducted in June 2004. We chose the banking industry given its long history of multichanneling which suggests a reasonable degree of familiarity with multiple channels among banking customers (Hitt & Frei 2002). As a qualifying criterion for inclusion in the sample, customers had to actively manage their financial affairs and had to be between 18 and 70 years of age. Each customer was interviewed face-to-face to ensure a clear understanding of the purpose of the study and of the questionnaire.

The behavioral characteristics in Table 2 indicate that the respondents maintain on average 1.6 bank connections and own 3.2 banking products. These values are similar to findings of previous studies and indicate the representativeness of the sample (Heise & Holzhausen 2004; Krah 2004).

Table 2 Behavioral Characteristics of the Sample

Characteristics	Sample Percentage
Number of bank connections	
1	56.2
2	35.6
3	6.2
4	1.0
5 and more	1.0
Number of banking products	
1	9.0
2	25.4
3	24.6
4	22.2
5 and more	18.8

The questionnaire consists of three parts. The first part is related to the channel usage behavior. Each respondent is asked for her past channel use and the future channel usage intention for ten different situations. These situations vary according to the three stages of the purchase process – the information, the purchase, and the transaction stage – and the products being considered. The products for the information and the purchase stage include the checking account, securities account, private loan, and investment fund. The products considered in the transaction stage are only the checking account and the securities account. The private loan and the investment fund are excluded for the transaction stage as these products do not require the customer to perform any transactions after the product has been purchased.

The options available as answers are different for the question regarding the past usage behavior and the future usage intention. In the case of the past usage behavior, respondents have to choose one of the available channels (branch, internet, call center, banking terminal) or a none-option. The none-option is included in case the respondent had never sought information, never purchased, or never used the considered product. The answers for the future channel usage intention are designed as constant sum scales. Hence, the respondents have the opportunity to distribute 100 points across the four available channels – the branch, the internet, the call center, and the banking terminal – according to the likelihood of usage in the given situation. A none-option is not included as a possible answer for the future channel usage intention as it is very unlikely that a respondent does not have an intention of which channel to use in case she had to search information on a product, purchase a product, or to use a previously purchased product.

The second part of the questionnaire is related to the perceived channel attributes of the branch, the internet, the call center, and the banking terminal. Each channel attribute is operationalized by multiple stage-specific items (see Appendix B). In line with previous research we exclude the channel attributes perceived price for the information stage and perceived quality for the transaction stage from the questionnaire (Boehm & Gensler 2006). The perceived price of the channel is not considered in the information stage due to the fact that information services are not priced in the German financial services market. The perceived quality is excluded from the questionnaire in the transaction stage as Boehm & Gensler (2006) find quality not to play a significant role in determining perceived channel value in the transaction stage. The items were administered as 5-point Likert scales ranging from 1 (absolutely disagree) to 5 (absolutely agree).

The third part of the questionnaire is concerned with the demographics of the respondents and their general interest in banking products and financial affairs.

5 Findings and Discussion

To identify the appropriate number of latent classes we use the Bayesian Information Criterion (BIC) resulting in a three segment solution.

In assessing the internal validity of the model, we calculate the correlation between the stated channel usage intentions and the estimated choice probabilities for all three stages of the purchase process (Hair et al. 2005). The results exhibit a highly significant correlation between observed and predicted choice probabilities indicating a high internal validity (information stage: 0.882, $p < 0.01$; purchase stage: 0.921, $p < 0.01$; transaction stage: 0.908, $p < 0.01$).

5.1 Channel Specific Factors

Table 3 presents the estimated coefficients and elasticities of the channel attributes across all three latent classes and stages of the purchase process.

All estimates are plausible. As expected the coefficients for the perceived quality and convenience indicate a positive influence on the choice of a channel whereas the perceived risk and price impact the choice negatively.

To examine whether the channel attributes differ in their impact on channel choice across customers we compare the elasticity rather than the coefficients of the channel attributes for the three latent classes (Louviere, Hensher, & Swait 2000, p. 57). The results for the information stage indicate that Class 1 only considers the perceived quality when choosing a channel. Class 2 and Class 3 on the other hand take the perceived quality, convenience, and risk into account. These two classes even show the same preference ranking for the channel attributes. In both cases the perceived quality receives the highest relevance when choosing a channel, followed by the perceived convenience and the perceived risk. Nevertheless, Class 2 and Class 3 differ in their elasticities they assign to the channel attributes.

Table 3: Coefficients and Elasticities of channel attributes

	Information stage			Purchase stage			Transaction stage		
	Class 1 (33.3%)	Class 2 (45.4%)	Class 3 (21.3%)	Class 1 (47.8%)	Class 2 (31.0%)	Class 3 (21.2%)	Class 1 (28.3%)	Class 2 (37.7%)	Class 3 (34.0%)
Quality	0.41 (0.89)	0.45 (1.14)	0.37 (0.86)	2.13 (4.24)	0.62 (2.16)	0.28 (0.85)			
Convenience	n.s.	0.21 (0.55)	0.20 (0.47)	0.30 (0.74)	0.17 (0.54)	0.27 (0.66)	0.47 (2.62)	1.09 (1.26)	0.39 (1.00)
Risk	n.s.	-0.14 (-0.27)	-0.06 (-0.11)	n.s.	-0.08 (-0.14)	-0.43 (-0.69)	-0.18 (-0.92)	-0.48 (-0.32)	-0.40 (-0.72)
Price				n.s.	-0.02 (-0.04)	n.s.	n.s.	n.s.	n.s.
N=500	Entropy R^2=0.997 ; BIC=266129			Entropy R^2=0.992; BIC=172032			Entropy R^2=0. 995; BIC=122116		

Note: Numbers without brackets represent coefficients and numbers within brackets represent the respective elasticity

The purchase stage shows a similar picture as in the information stage. Again the perceived quality is an important factor influencing the respondents' channel choice. In addition to the perceived quality, only the perceived convenience influences the channel choice of Class 1. The risk and the price perception show no significant impact. Class 2 on the other hand considers all channel attributes when choosing a channel. It assigns the highest relevance to the perceived quality, followed by the perceived convenience, risk, and price. This importance structure is slightly reversed for Class 3. Respondents in Class 3 attach a higher elasticity to the perceived risk than to the perceived convenience when choosing a channel. The price has no significant impact for this class.

The results for the transaction stage are characterized by the insignificant coefficients for the perceived price across all three latent classes. Only the perceived convenience and the perceived risk influence channel choice in the transaction stage. For all three latent classes the convenient use of a channel has a stronger impact on channel choice than the perceived risk of a channel. This might be primarily due to the fact that all available channels are perceived to have a similar risk level in the transaction stage.

5.2 Situation Specific Factors

The results in Table 3 indicate furthermore that the impact on channel choice of certain channel attributes differs across the three stages of the purchase process. For instance convenience has a medium impact on channel choice for the information and the purchase stage whereas it has a major impact on channel choice in the transaction stage. Hence, it can be concluded that the stage of the purchase process has a moderating impact on channel choice. Even the importance of the considered channel attributes varies across the stages of the purchase process. Neglecting the moderating impact of the stages of the purchase process would therefore lead to wrong conclusions about a customer's channel choice behavior.

An impact of the product being considered on channel choice could not be confirmed. This finding is contrary to the results of Morrison & Roberts (1998). The missing influence of the product on channel choice might be due to the selection of products considered in the study. The products were chosen due to their high penetration in the market to ensure reliable answers. As a result of this selection process, all products can be classified as products with a low complexity and a low associated risk. The limited dissimilarity between the various products might have resulted in this insignificant impact.

5.3 Customer Specific Factors

The estimated model allows as well to test whether the customer specific variables have an impact on a customer's channel choice.

Table 4 summarizes the intrinsic preference structure for the three latent classes across the three stages of the purchase process as estimated by the latent class MNL. The results indicate a distinct preference structure for the three latent classes. Class 1 can be described as the branch segment as it shows by far the highest preference for the incumbent channel. Class 2 has a preference for the branch and the internet whereas the preference for the branch exceeds the preference for the internet. It therefore can be regarded as the multi-channel segment. Finally, Class 3 exhibits constantly the highest preference for the internet across all three stages of the purchase process. Hence, Class 3 can be described as the internet segment.

Table 4: Intrinsic Preference and Channel Experience

	Information stage			**Purchase stage**			**Transaction stage**		
	Class 1 (33.3%)	Class 2 (45.4%)	Class 3 (21.3%)	Class 1 (47.8%)	Class 2 (31.0%)	Class 3 (21.2%)	Class 1 (28.3%)	Class 2 (37.7%)	Class 3 (34.0%)
Branch	2.31	1.00	n.s.	5.81	1.86	0.54	4.01	3.31	0.31
Call Center	-1.33	-0.15	-0.94	0.05	-0.19	-0.23	-1.93	-4.52	-0.13
Internet	-0.32	0.33	1.16	-0.52	0.50	0.82	-1.18	1.74	0.40
Banking Terminal	-0.65	-1.18	-0.21	-5.80	-2.18	-1.14	-0.90	-0.53	-0.58
Within-stage experience	1.84	0.14	0.67	-0.06	0.17	n.s.	0.91	1.81	0.42
Between-stage experience				0.30	0.24	0.29	-2.80	n.s.	-0.25

The second half of Table 4 presents the impact of a customer's channel experience on channel choice. The mostly positive coefficients for the within-stage experience indicate that customers are loyal to a channel. This confirms the hypothesis that the more often a channel is chosen by a customer the higher the likelihood that this channel is chosen again next time. The between-stage experience indicates a positive carry-over effect from the information to the purchase stage. Customers who seek information through a channel are more likely as well to purchase the product through the same channel which supports the results by Ward & Morganosky (2002). This relationship is reversed for the impact of the channel use in the purchase stage on the channel usage in the transaction stage. One explanation might be that the purchase stage coincides in many cases with the information stage whereas it does not with the transaction stage.

The results furthermore show that there are no demographic or behavioral variables which significantly discriminate between all three identified latent classes. It can therefore be concluded that demographic variables do not have a significant impact on channel choice. This supports the findings of Akaah, Korgaonkar, & Lund (1995) who do not identify any demographic differences between in-home shoppers and non-in-home shoppers. Similarly the longitudinal WWW survey by the GVU Center shows a constant assimilation of the demographics between internet users and the average population over time (GVU Center 2001).

6 Approach to Predict the Impact of Channel Migration on Channel Usage and Customer Profit Contribution

The developed channel choice model and the estimated results can now be leveraged to make predictions about the impact of customer channel migration on a customer's channel usage behavior and hence on the resulting cost reductions. As a result the return on investment for channel migration measures which intend to alter a customer's perception of certain channel attributes can be determined.

6.1 Predict Impact of Channel Migration Measures on Channel Usage Behavior

In order to make predictions about the impact of channel migration measures on customer channel usage behavior it is essential to model the channel switching behavior of a customer – the channel usage before and after a channel migration measure. This allows to identify changes in customer channel usage behavior due to channel migration measures.

One approach to model channel switching behavior and to relate it to channel migration measures are transition probability matrices as proposed by Zufryden (1981). He demonstrates that a MNL framework can be used to relate explanatory variables to transition probabilities. A change in the explanatory variables, for instance due to certain channel migration measures, will lead to a change in the transition probability matrix (Rust, Lemon, & Zeithaml 2004). These findings indicate that the estimated channel choice model can be used to determine the necessary transition probabilities to make predictions about the impact of channel migration measures.

A greater extent of customer heterogeneity might make it necessary to investigate individual channel switching behavior in order to develop meaningful customer channel migration strategies. The estimation of individual transition probability matrices allows to evaluate whether channel migration measures should be applied to a specific customer or not. Deriving individual transition probability matrices can be achieved by deriving the posteriori probabilities of the latent class channel choice model. To determine individual coefficients and hence individual transition probability matrices a multiplication of a customer's class membership probabilities times the estimated segment specific coefficients has to be performed (Vriens, Oppewal, & Wedel 1998).

6.2 Predict Impact of Channel Migration on a Customer's Profit Contribution

To see how a transition probability matrix relates to a customer's profit contribution, let us consider a simplified example. An average customer generates in each period revenues of $ 100. At the same time the customer generates costs by interacting with the bank. On average the customer conducts 100 transactions in each period. The bank offers the customer two channels to interact with the bank: the branch and the internet. The costs incurred by the bank per transaction are $ 1 and $ 0.1 respectively. Currently, the customer uses in 60% of the cases the branch and in 40% of the cases the internet. This leaves a profit of $ 36 $\left[\$100 - (60 \cdot \$1 + 40 \cdot \$0.1) = \$36\right]$ for the bank.

By means of channel migration the bank aims to influence the channel mix used by the customer and invests $ 10 per customer. The customer now uses in only 40% of the transactions the branch and in the remaining 60% the internet. This generates a new profit contribution by the customer of $ 54 $\left[\$100 - \left(40 \cdot \$1 + 60 \cdot \$0.1\right) = \$54\right]$. The migration measure has therefore produced an ROI of 180% $\left[\left(\$54 - \$36\right) : \$10 = 1.8\right]$ for an average customer. To determine the overall profit impact of this channel migration measure it would now be necessary to multiply the profit contribution per customer times the number of customers.

7 Simulate the Impact of Channel Migration on Channel Usage and Customer Profit Contribution

A customer channel migration strategy has to answer two basic questions: (1) Which channel mix maximizes a customer's profit contribution? (2) Which migration measures should be used to influence a customer's channel usage towards the profit maximizing channel mix?

Regarding the first question, some researchers have investigated the relationship of costs incurred by the bank and channels used by the customer (Myers, Pickersgill, & Van Metre 2004; Kumar & Venkatesan 2005). This research has shown that especially the increasing usage of the internet reduces the overall costs generated by a customer. This would suggest that a migration strategy should influence customers to increasingly use the internet channel.

Regarding the second question, three groups of factors influencing channel choice decisions have been identified by our study: channel specific factors, situation specific factors, and customer specific factors. Customer specific factors such as the intrinsic channel preference and the channel experience impact the channel choice of a customer but can not be managed by the bank. For instance, a bank is not able to influence the level of experience a customer has gathered with a certain channel. This can only be achieved in the long-run by attracting customers with a certain channel experience structure. The same is true for situation specific factors. Customers first choose the situation driven by their financial needs and accordingly choose the appropriate channel. Thus, banks can impact a customer's channel usage only by influencing a customer's perception of the channels.

Two scenarios will be evaluated in the following simulation study. The first scenario entails a customer channel migration strategy which is designed to increase the usage of the internet in the information stage. The first scenario assumes that it is possible to increase the perceived quality and convenience of the internet among the customers on average by 20%. The second scenario aims to increase the use of the internet not only in the information, but as well in the transaction stage. The scenario therefore evaluates the impact of the assumption that the perceived quality and convenience of the internet in the information stage can be improved by 20% and in addition that the perceived convenience of the internet in the transaction stage can be improved by 20% (see Table 5).

Table 5 Assumptions of Simulation for the Customer Channel Migration Strategy

Purchase Process Stage	Scenario 1	Scenario 2
Information	▪ Increase of the perceived quality of the internet by 20% among the considered customers ▪ Increase of the perceived convenience of the internet by 20% among the considered customers	▪ Increase of the perceived quality of the internet by 20% among the considered customers ▪ Increase of the perceived convenience of the internet by 20% among the considered customers
Purchase	-	-
Transaction	-	▪ Increase of the perceived convenience of the internet by 20% among the considered customers

Evaluating the success of the migration strategy requires to estimate the financial impact of the proposed measures. In order to predict the financial impact some assumptions about the cost structure of each channel have to be made. To simplify the simulation study, we only simulate the cost savings which can be achieved by managing a customer's channel usage for the checking account product. The cost structure for each channel across the different stages of the purchase process is illustrated in Table 6. We assume further that each customer will seek information about checking accounts only once. The same is true for the actual purchase of the product. In the transaction stage on the other hand, the customer will conduct on average 120 transactions per year. The simulation study will estimate the financial impact of the proposed customer channel migration strategy for 400.000 customers interested in a checking account.

Table 6 Channel Cost Structure

Purchase Process Stage	# of transactions per year	Branch	Internet	Call Center	Banking Terminal
Information	1	$ 15.00	$ 1.00	$ 10.00	$ 3.00
Purchase	1	$ 30.00	$ 3.00	$ 20.00	$ 5.00
Transaction	120	$ 1.07	$ 0.01	$ 0.54	$ 0.27

Source: Booz Allen & Hamilton 1996

The costs generated by these 400.000 customers before and after raising the perception of the channel attributes are presented in Table 7.

The costs in the branch, the call center, and the banking terminal can be reduced in both scenarios across all three stages of the purchase process by improving the perception of the internet channel. At the same time the costs incurred in the internet channel increase due to the grown internet usage. Nevertheless, the cost increase in the internet is easily compensated by the cost reductions in the other channels. The scenarios achieve overall cost reductions of $ 344.649 and $ 1.786.337 respectively which appear to be valid results according to expert opinions (see Table 7). Hence, both migration scenarios result in a positive profit contribution when not considering investments for the migration measures.

Table 7 Financial Impact of Migration Measures

	Scenario 1				Scenario 2			
	Information Stage				**Information Stage**			
	Branch	**Internet**	**CC**	**BT**	**Branch**	**Internet**	**CC**	**BT**
Before Simulation	2.500.218	105.438	668.629	183.054	2.500.218	105.438	668.629	183.054
After Simulation	2.309.496	129.562	609.050	166.701	2.309.496	129.562	609.050	166.701
Change	-190.722	24.124	-59.579	-16.353	-190.722	24.124	-59.579	-16.353
Change per Stage				-242.530				-242.530
	Purchase Stage				**Purchase Stage**			
	Branch	**Internet**	**CC**	**BT**	**Branch**	**Internet**	**CC**	**BT**
Before Simulation	5.771.311	302.564	1.088.780	261.647	5.771.311	302.564	1.088.780	261.647
After Simulation	5.666.824	315.167	1.079.921	260.271	5.666.824	315.167	1.079.921	260.271
Change	-104.487	12.603	-8.859	-1.376	-104.487	12.603	-8.859	-1.376
Change per Stage				-102.119				-102.119
	Transaction Stage				**Transaction Stage**			
	Branch	**Internet**	**CC**	**BT**	**Branch**	**Internet**	**CC**	**BT**
Before Simulation	12.917.630	156.610	4.159.911	3.391.995	12.917.630	156.610	4.159.911	3.391.995
After Simulation	12.917.630	156.610	4.159.911	3.391.995	12.085.078	180.928	3.786.007	3.132.445
Change	0	0	0	0	-832.552	24.318	-373.904	-259.550
Change per Stage				0				-1.441.688
Total Change				**-344.649**				**-1.786.337**

8 Conclusions and Managerial Implications

The aim of this paper was to predict the impact of channel migration measures on customer channel usage behavior and on the resulting cost reductions.

By pursuing this objective we developed a model describing the customer channel choice behavior across different stages of the purchase process. The literature review and the estimated model have shown that channel choice is influenced by channel, situation, and customer specific factors. The main drivers of channel choice are the channel specific factors with their direct impact on perceived channel value. Channel specific factors are as well the only factors influencing the channel choice which are under the direct control of a bank.

Hence, migration strategies have to rely on channel specific factors to impact a customer's channel usage behavior. Customer and situation specific factors function as moderating factors on the perceived channel value and can be used to better target migration strategies.

Estimation results of the channel choice model have identified as well the factors with the strongest impact on channel choice. It was determined that the perceived quality is the most important driver influencing channel choice in the information and the purchase stage. The perceived convenience has been identified as the most important driver in the transaction stage. Migration strategies can build upon these insights in order to ensure their effectiveness.

Finally, the paper proposed an approach to estimate the impact of migration strategies on channel usage behavior and a customer's profit contribution which allows to determine the return on channel investments. A simulation study did exhibit significant cost savings which can be achieved through customer channel migration. The insights generated by the simulation study can readily be applied in order to increase a customer's profit contribution.

The findings presented in this paper are based on a model which is the first to model the channel choice in the presence of multiple channels and multiple stages of the purchase process. Furthermore, it is the first to consider a comprehensive set of factors influencing channel choice decisions.

However, this research is subject to several limitations. Although we studied the impact of four products on a customer's channel choice, these products appear to be limited in terms of being distinct from each other. Hence, future research might be extended to include banking products characterized by higher levels of complexity and associated risk. Similarly, it might be interesting whether our results can be replicated in other industries as we used only data from the banking industry. Nevertheless, we are confident that our approach can easily be applied as well to other industries.

In summary, we contribute to the literature by developing a comprehensive model to predict a customer's channel usage behavior and respective cost reductions. This offers multichannel managers the opportunity to predict the profit impact of alternative channel migration strategies and hence to find a strategy which maximizes a firm's profitability.

9 References

Akaah, I. P., Korgaonkar, P. K., & Lund, D. (1995). Direct Marketing Attitudes. *Journal of Business Research*, 34, 211-219.

Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentive to Participate in Electronic Marketplaces. *Journal of Marketing*, 61, 38-53.

Anderson, S., & Lanen, W. (2002). Using Electronic Data Interchange (EDI) to Improve the Efficiency of Accounting Transactions. *The Accounting Review*, 77, 703-730.

Ansari, A., Mela, C., & Neslin, S. (2005). *Customer Channel Migration*. Working Paper, Columbia University, New York.

Balabanis, G., & Vassileiou, S. (1999). Some Attitudinal Predictors of Home-Shopping Through the Internet. *Journal of Marketing Management*, 15, 361-385.

Balasubramanian, S. (1998). Mail Versus Mall: A Strategic Analysis of Competition Between Direct Marketers and Conventional Retailers. *Marketing Science*, 17, 181-195.

Balasubramanian, S., Raghunathan, R., & Mahajan, V. (2005). Consumers in a Multichannel Environment: Product Utility, Process Utility, And Channel Choice. *Journal of Interactive Marketing*, 19, 12-30.

Barczak, G., Scholder Ellen, P., & Pilling, B. K. (1997). Developing Typologies of Consumer Motives for Use of Technologically Based Banking Services. *Journal of Business Research*, 38, 131-139.

Black, N. J., Lockett, A., Ennew, C., Winklhofer, H., & McKechnie, S. (2002). Modelling Consumer Choice Of Distribution Channels: An Illustration from Financial Services. *International Journal of Bank Marketing*, 20, 161-173.

Boehm, M., & Gensler, S. (2006). *Measuring Perceived Channel Value*. Working Paper, Johann Wolfgang Goethe-Universität, Frankfurt.

Booz Allen & Hamilton (1996). *Internet Banking: A Survey of Current and Future Development*. White Paper, New York: Financial Services Group.

Citrin, A. V., Stem, D. E., Spangenberg, E. R., & Clark, M. J. (2003). Consumer Need for Tactile Input: An Internet Retailing Challenge. *Journal of Business Research*, 56, 915-922.

Crask, M., & Reynolds, F. (1978). An Indepth Profile of the Department Store Shopper. *Journal of Retailing*, 54, 23-32.

Cunningham, S. M. (1967). The Major Dimensions of Perceived Risk. In D. F. Cox (Ed.), *Risk Taking and Information Handling in Consumer Behavior* (pp. 82-108). Boston: Harvard University Press.

Darian, J., Wiman, A., & Tucci, L. (2005). Retail Patronage Intentions: The Relative Importance Of Perceived Prices And Salesperson Service Attributes. *Journal of Retailing and Consumer Services*, 12, 15-23.

Darian, J. C. (1987). In-Home Shopping: Are There Consumer Segments? *Journal of Retailing*, 63, 163-186.

Degeratu, A., Rangaswamy, A., & Wu, J. (2000). Consumer Choice Behaviour in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes. *International Journal of Research in Marketing*, 17, 55-78.

Devlin, J. F. (2002). Customer Knowledge and Choice Criteria in Retail Banking. *Journal of Strategic Marketing*, 10, 273-290.

Devlin, J. F., & Yeung, F. T. (2003). Insights into Customer Motivations for Switching to Internet Banking. *International Review of Retail, Distribution and Consumer Research*, 13, 375-392.

Dholakia, R. R., & Uusitalo, O. (2002). Switching to Electronic Stores: Consumer Characteristics and the Perception of Shopping Benefits. *International Journal of Retail & Distribution Management*, 30, 459-469.

Donthu, N., & Garcia, A. (1999). The Internet Shopper. *Journal of Advertising Research*, 39, 52-58.

Durkin, M., McCartan-Quinn, D., O'Donnell, A., & Howcroft, B. (2003). Retail Bank Customer Preference: Personal and Remote Interactions. *International Journal of Retail & Distribution Management*, 31, 177-189.

Eastlick, M. A., & Feinberg, R. A. (1999). Shopping Motives for Mail Catalog Shopping. *Journal of Business Research*, 45, 281-290.

Eastlick, M. A., & Liu, M. (1997). The Influence of Store Attitudes and other Non-Store Shopping Patterns on Patronage of Teleshopping. *Journal of Direct Marketing*, 11, 14-25.

Fader, P. S., Hardie, B., & Lee, K. L. (2005). "Counting Your Customers" The Easy Way: An Alternative to the Pareto/NBD Model. *Marketing Science*, 24, 275-284.

Filotto, U., Tanzi, P. M., & Saita, F. (1997). Customer Needs and Front-Office Technology Adoption. *International Journal of Bank Marketing*, 15, 13-21.

Forsythe, S., Liu, C., Shannon, D., & Gardner, L. C. (2006). Development of a Scale to Measure the Perceived Benefits and Risks of Online Shopping. *Journal of Interactive Marketing*, 20, 55-75.

Gehrt, K., & Yale, L. J. (1996). The Convenience of Catalog Shopping: Is there more to it than Time? *Journal of Direct Marketing*, 10, 19-29.

Gehrt, K. C., Ingram, T. N., & Howe, V. (1988). Past Non-Store Patronage as a Covariate. A Reassessment of Individual Traits as Predictors of Non-Store Patronage. *Journal of Direct Marketing*, 2, 16-25.

Gillett, P. L. (1976). In-Home Shoppers - An Overview. *Journal of Marketing*, 40, 81-88.

Grewal, D., Levy, M., & Marshall, G. W. (2002). Personal Selling in Retail Settings: How Does the Internet and Related Technologies Enable and Limit Successful Selling? *Journal of Marketing Management*, 18, 301-316.

Gronroos, C. (1984). A Service Quality Model and Its Marketing Implications. *European Journal of Marketing*, 18, 36-44.

Gupta, A., Su, B.-C., & Walter, Z. (2004). An Empirical Study of Consumer Switching from Traditional to Electronic Channels: A Purchase-Decision Perspective. *International Journal of Electronic Commerce*, 8, 131-161.

GVU Center (2001). *GVU's WWW User Surveys*. Retrieved 10th of January 2006, from http://www.cc.gatech.edu/gvu/user_surveys/.

Hair, J. F., Black, B., Babin, B., Anderson, R. E., & Tatham, R. L. (2005). *Multivariate Data Analysis*. Upper Saddle River: Prentice Hall.

Hawes, J. M., & Lumpkin, J. R. (1986). Perceived Risk and the Selection of a Retail Patronage Mode. *Journal of the Academy of Marketing Science*, 14, 37-42.

Heise, M., & Holzhausen, A. (2004). *Germany's Banks: Overview and International Comparison*. White Paper, München: Allianz Group.

Hitt, L. M., & Frei, F. X. (2002). Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking. *Management Science*, 48, 732-748.

Hitt, L. M., Frei, F. X., & Harker, P. (1999). How Financial Firms Decide on Technology. In R. E. Litan, & A. M. Santomero (Eds.), *Brookings Wharton Papers on Financial Services* (pp. 93-146). Washington: Brookings Institution.

Hoffman, K. (2002). Online Banking Aligns Practices: Now That The Initial Online Flurry Has Subsided, Web-based Banks Are Looking At ROI Potential. *Bank Technology News*, 26-29.

Inman, J. J., Shankar, V., & Ferraro, R. (2004). The Roles of Channel-Category Associations and Geodemographics in Channel Patronage. *Journal of Marketing*, 68, 51-71.

Kacen, J., Hess, J., & Chiang, W. K. (2005). *Bricks or Clicks? Consumer Attitudes Toward Traditional Stores and Online Stores*. Working Paper, University of Houston, Houston.

Kamakura, W. A., & Russell, G. J. (1989). A Probabilistic Choice Model for Market Segmentation and Elasticity Structuring. *Journal of Marketing Research*, 26, 379-390.

Kaufman-Scarborough, C., & Lindquist, J. D. (2002). E-Shopping in a Multiple Channel Environment. *Journal of Consumer Marketing*, 19, 333-350.

Keeney, R. (1999). The Value of Internet Commerce to the Customer. *Management Science*, 45, 533-542.

Korgaonkar, P. K., Lund, D., & Price, B. (1985). A Structural Equations Approach Toward Examination of Store Attitude and Store Patronage. *Journal of Retailing*, 61, 39-60.

Korgaonkar, P. K., & Wolin, L. D. (1999). A Multivariate Analysis of Web Usage. *Journal of Advertising Research*, 53-68.

Krah, E.-S. (2004). Den Kunden als Ganzes sehen [A Holistic View of the Customer]. *Bankmagazin*, 35-37 (in German).

Kumar, V., Aaker, D. A., & Day, G. S. (2002). *Essentials of Marketing Research*. New York: John Wiley & Sons.

Kumar, V., & Venkatesan, R. (2005). Who Are The Multichannel Shoppers And How Do They Perform?: Correlates Of Multichannel Shopping Behavior. *Journal of Interactive Marketing*, 19, 44-62.

Kwak, H., Fox, R., & Zinkhan, G. M. (2002). What Products Can be Successfully Promoted and Sold via the Internet? *Journal of Advertising Research*, 42, 23-38.

Lee, J. (2002). A Key to Marketing Financial Services: The Right Mix of Products, Services, Channels and Customers. *Journal of Services Marketing*, 16, 238-258.

Lee, K. S., & Tan, S. J. (2003). E-Retailing versus Physical Retailing: A Theoretical Model and Empirical Test of Consumer Choice. *Journal of Business Research*, 56, 877-885.

Liang, T.-P., & Huang, J.-S. (1998). An Empirical Study on Consumer Acceptance of Products in Electronic Markets: A Transaction Cost Model. *Decision Support Systems*, 24, 29-43.

Lockett, A., & Littler, D. (1997). The Adoption of Direct Banking Services. *Journal of Marketing Management*, 13, 791-811.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated Choice Methods: Analysis and Application*. Cambridge: Cambridge University Press.

Mattila, M. (2002). Introducing Existing Financial Services over New Electronic Channels. *International Journal of Innovation Management*, 6, 431-447.

Mattson, B. E. (1982). Situational Influence on Store Choice. *Journal of Retailing*, 58, 46-58.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behaviour. In I. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105-142). New York: Academic Press.

Montoya-Weiss, M. M., Voss, G. V., & Grewal, D. (2003). Determinants of Online Channel Use and Overall Satisfaction with a Relational, Multichannel Service Provider. *Journal of the Academy of Marketing Science*, 31, 448-458.

Moon, B.-J. (2004). Consumer Adoption of the Internet as Information Search and Product Purchase Channel: Some Research Hypotheses. *International Journal of Internet Marketing and Advertising*, 1, 104-118.

Morrison, P. D., & Roberts, J. H. (1998). Matching Electronic Distribution Channels to Product Characteristics: The Role of Congruence in Consideration Set Formation. *Journal of Business Research*, 41, 223-229.

Myers, J., Pickersgill, A., & Van Metre, E. (2004). Steering Customers to the Right Channels. *McKinsey Quarterly*, 2004, 36-47.

Nicholson, M., Clarke, I., & Blakemore, M. (2002). One Brand, Three Ways to Shop: Situational Variables and Multichannel Consumer Behaviour. *International Review of Retail, Distribution and Consumer Research*, 12, 131-148.

Palmer, J. W. (2000). Electronic Commerce in Retailing: Convenience, Search Costs, Delivery and Price Across Retail Formats. *Information Technology & Management Journal*, 1, 25-43.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing*, 64, 12-40.

Peters, W. H., & Ford, N. M. (1972). A Profile of Urban In-Home Shoppers: The Other Half. *Journal of Marketing*, 36, 62-64.

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer Acceptance of Online Banking: An Extension of the Technology Acceptance Model. *Internet Research*, 14, 224-235.

Prasad, B., & Harker, P. (2000). *Pricing Online Banking Services Amid Network Externalities*. Paper presented at the 33rd Hawaii International Conference on System Sciences, Hawaii, USA.

Raijas, A., & Tuunainen, V. K. (2001). Critical Factors in Electronic Grocery Shopping. *International Review of Retail, Distribution and Consumer Research*, 11, 255-265.

Ramaswami, S. N., Strader, T. J., & Brett, K. (2001). Determinants of On-Line Channel Use for Purchasing Financial Products. *International Journal of Electronic Commerce*, 5, 95-118.

Ramsay, J., & Smith, M. (1999). Managing Customer Channel Usage in the Australian Banking Sector. *Managerial Auditing Journal*, 14, 329-338.

Rangaswamy, A., & Van Bruggen, G. H. (2005). Opportunities and Challenges in Multichannel Marketing: An Introduction to the Special Issue. *Journal of Interactive Marketing*, 19, 5-11.

Rasch, S., & Lintner, A. (2001). *The Multichannel Consumer: The Need To Integrate Online and Offline Channels In Europe*. White Paper, Boston: Boston Consulting Group.

Ratchford, B. T., Lee, M.-S., & Talukdar, D. (2003). The Impact of the Internet on Information Search for Automobiles. *Journal of Marketing Research*, 40, 193-209.

Reardon, J., & McCorkle, D. (2002). A Consumer Model for Channel Switching Behaviour. *International Journal of Retail & Distribution Management*, 30, 179-185.

Rugimbana, R., & Iversen, P. (1994). Perceived Attributes of ATMs and their Marketing Applications. *International Journal of Bank Marketing*, 12, 30-35.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on Marketing: Using Customer Equity to Focus Marketing Strategy. *Journal of Marketing*, 68, 109-127.

Schoenbachler, D. D., & Goeffrey, G. L. (2002). Multi-Channel Shopping: Understanding What Drives Channel Choice. *Journal of Consumer Marketing*, 19, 42-53.

Sindhav, B., & Balazs, A. L. (1999). A Model of Factors Affecting the Growth of Retailing on the Internet. *Journal of Market Focused Management*, 4, 319-339.

Singh, V. P., Hansen, K. T., & Gupta, S. (2005). Modeling Preferences for Common Attributes in Multicategory Brand Choice. *Journal of Marketing Research*, 42, 195-209.

Sorce, P., Perotti, V., & Widrick, S. (2005). Attitude and Age Differences in Online Buying. *International Journal of Retail & Distribution Management*, 33, 122-132.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer Loyalty in E-Commerce: An Exploration of its Antecedents and Consequences. *Journal of Retailing*, 78, 41-50.

Stone, R. N., & Gronhaug, K. (1993). Perceived Risk: Further Considerations for the Marketing Discipline. *European Journal of Marketing*, 27, 39-50.

Strebel, J., Erdem, T., & Swait, J. (2004). Consumer Search in High Technology Markets: Exploring the Use of Traditional Information Channels. *Journal of Consumer Psychology*, 14, 96-104.

Teo, T., S.H., Leong, C. H., & Wang, P. (2004). Understanding Online Shopping Behaviour Using a Transaction Cost Economics Approach. *International Journal of Internet Marketing and Advertising*, 1, 62-84.

Thomas, J. S., & Sullivan, U. Y. (2005). Managing Marketing Communications with Multichannel Customers. *Journal of Marketing*, 69, 239-251.

Thornton, J., & White, L. (2001). Customer Orientations and Usage of Financial Distribution Channels. *Journal of Services Marketing*, 15, 168-185.

Torkzadeh, G., & Dhillon, G. (2002). Measuring Factors that Influence the Success of Internet Commerce. *Information Systems Research*, 13, 187-204.

Tse, A. C. B., & Yim, F. (2001). Factors Affecting The Choice of Channels: Online vs Conventional. *Journal of International Consumer Marketing*, 14, 137-153.

Van Baal, S., & Dach, C. (2005). Free Riding And Consumer Retention Across Retailers' Channels. *Journal of Interactive Marketing*, 19, 75-85.

Van den Poel, D., & Leunis, J. (1999). Consumer Acceptance of the Internet as a Channel of Distribution. *Journal of Business Research*, 45, 249-256.

Vermunt, J. K., & Magidson, J. (2004). *Latent Gold Choice 4.0 User's Manual*. White Paper, Belmont: Statistical Innovations.

Vriens, M., Oppewal, H., & Wedel, M. (1998). Ratings-Based Versus Choice-Based Latent Class Conjoint Models - An Empirical Comparison. *Journal of the Market Research Society*, 40, 237-248.

Ward, M. R. (2001). Will Online Shopping Compete more with Traditional Retailing or Catalog shopping? *Netnomics*, 3, 103-117.

Ward, M. R., & Morganosky, M. (2002). Consumer Acquisition of Product Information and Subsequent Purchase Channel Decisions. In M. R. Baye (Ed.), *The Economics of the Internet and E-Commerce* (pp. 231-256). Amsterdam: Elsevier Science.

Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing*, 52, 2-22.

Zeithaml, V. A., & Gilly, M. C. (1987). Characteristics Affecting the Acceptance of Retailing Technologies: A Comparison of Elderly and Nonelderly Consumers. *Journal of Retailing*, 63, 49-68.

Zufryden, F. S. (1981). A Logit-Markovian Model of Consumer Purchase Behaviour Based on Explanatory Variables: Empirical Evaluation and Implications For Decision Making. *Decision Sciences*, 12, 645-660.

Appendix A Literature Review on Channel Choice Factors

Author	Literature Stream	Empirical	Channel Specific				Situation Specific		Customer Specific		
			Convenience	Quality	Risk	Price	Process Stage	Product Specific	Channel Preferences	Channel Experience	Demographics
Barczak, Scholder Ellen, & Pilling 1997	Descriptive	+	-	-	-	-	-	-	-	-	+
Black et al. 2002	Descriptive	+	+	+	+	+	+	+	+	+	+
Donthu & Garcia 1999	Descriptive	+	-	-	-	-	-	-	-	-	+
Hawes & Lumpkin 1986	Descriptive	+	-	-	+	-	-	-	-	-	-
Keeney 1999	Descriptive	+	+	+	+	+	-	-	-	-	-
Lee & Tan 2003	Descriptive	+	-	-	+	-	-	+	-	-	-
Nicholson, Clarke, & Blakemore 2002	Descriptive	+	-	-	-	-	+	+	-	-	-
Palmer 2000	Descriptive	+	+	+	-	+	-	-	-	-	-
Raijas & Tuunainen 2001	Descriptive	+	+	+	-	+	-	-	-	-	-
Ramsay & Smith 1999	Descriptive	+	+	-	-	+	-	-	-	-	-
Torkzadeh & Dhillon 2002	Descriptive	+	+	+	+	+	-	-	-	-	-
Gillett 1976	Literature Review	+	+	-	+	-	-	-	-	-	+
Alba et al. 1997	Conceptual	-	+	+	-	+	-	-	-	-	-
Grewal, Levy, & Marshall 2002	Conceptual	-	+	-	+	+	-	-	-	-	-
Reardon & McCorkle 2002	Conceptual	-	+	+	+	+	-	-	-	-	-
Schoenbachler & Goeffrey 2002	Conceptual	-	-	-	+	-	-	+	+	+	-
Sindhav & Balazs 1999	Conceptual	-	+	+	+	-	+	+	+	+	-
Balabanis & Vassileiou 1999	Channel Adoption	+	-	-	-	-	-	+	-	+	+
Citrin et al. 2003	Channel Adoption	+	-	-	-	-	-	+	-	+	-
Darian 1987	Channel Adoption	+	+	-	+	-	-	+	-	-	+
Degeratu, Rangaswamy, & Wu 2000	Channel Adoption	+	-	-	-	-	-	-	-	-	+
Devlin & Yeung 2003	Channel Adoption	+	-	+	-	-	-	-	-	-	+

Appendix A (Continued): Literature Review on Channel Choice Factors

			Channel Specific				Situation Specific		Customer Specific		
Author	Literature Stream	Empirical	Convenience	Quality	Risk	Price	Process Stage	Product Specific	Channel Preferences	Channel Experience	Demographics
Dholakia & Uusitalo 2002	Channel Adoption	+	-	-	-	-	-	-	-	+	+
Durkin et al. 2003	Channel Adoption	+	-	+	-	-	-	-	-	-	-
Eastlick & Feinberg 1999	Channel Adoption	+	+	+	+	+	-	+	-	-	-
Filotto, Tanzi, & Saita 1997	Channel Adoption	+	+	-	-	+	-	-	-	-	-
Gupta, Su, & Walter 2004	Channel Adoption	+	+	-	+	-	+	-	-	-	+
Inman, Shankar, & Ferraro 2004	Channel Adoption	+	-	-	-	-	-	+	-	-	+
Kacen, Hess, & Chiang 2005	Channel Adoption	+	+	-	+	+	-	+	-	+	+
Kaufman-Scarborough & Lindquist 2002	Channel Adoption	+	+	-	-	-	+	-	-	-	+
Korgaonkar & Wolin 1999	Channel Adoption	+	-	-	+	+	-	-	-	-	+
Kwak, Fox, & Zinkhan 2002	Channel Adoption	+	-	-	-	-	-	+	-	+	+
Lee 2002	Channel Adoption	+	-	-	-	-	-	+	+	-	+
Liang & Huang 1998	Channel Adoption	+	+	-	+	+	-	+	-	+	+
Lockett & Littler 1997	Channel Adoption	+	+	-	+	-	-	-	-	-	+
Mattila 2002	Channel Adoption	+	+	+	+	+	-	-	-	-	+
Montoya-Weiss, Voss, & Grewal 2003	Channel Adoption	+	-	+	+	-	-	-	-	+	-
Moon 2004	Channel Adoption	+	+	+	+	+	+	+	-	+	+
Morrison & Roberts 1998	Channel Adoption	+	+	+	+	-	-	+	+	-	-
Pikkarainen et al. 2004	Channel Adoption	+	+	+	+	-	-	-	-	-	-
Ramaswami, Strader, & Brett 2001	Channel Adoption	+	-	-	-	-	+	-	+	+	+
Ratchford, Lee, & Talukdar 2003	Channel Adoption	+	-	-	-	+	+	+	-	+	+
Rugimbana & Iversen 1994	Channel Adoption	+	+	+	+	-	-	-	-	-	-
Sorce, Perotti, & Widrick 2005	Channel Adoption	+	+	+	-	-	-	-	-	-	+

Appendix A (Continued): Literature Review on Channel Choice Factors

			Channel Specific				Situation Specific		Customer Specific		
Author	Literature Stream	Empirical	Convenience	Quality	Risk	Price	Process Stage	Product Specific	Channel Preferences	Channel Experience	Demographics
Teo, Leong, & Wang 2004	Channel Adoption	+	+	+	+	+	-	-	-	-	-
Thornton & White 2001	Channel Adoption	+	+	+	+	-	-	-	-	-	-
Tse & Yim 2001	Channel Adoption	+	+	+	+	+	-	+	-	-	-
Van den Poel & Leunis 1999	Channel Adoption	+	-	-	+	-	+	+	-	-	-
Ward 2001	Channel Adoption	+	-	-	-	-	+	+	-	+	-
Zeithaml & Gilly 1987	Channel Adoption	+	+	+	+	-	-	-	-	-	+
Strebel, Erdem, & Swait 2004	Channel Adoption	+	-	-	-	-	-	-	-	-	+
Thomas & Sullivan 2005	Channel Adoption	+	-	-	-	+	-	+	-	+	-

Appendix B Scale Measuring Perceived Channel Value

Item
Information
Quality
The information offered on this channel satisfies all my needs.
The information offered meets my expectations.
On this channel I receive individualized information.
Convenience
The channel design eases the search for information.
This channel offers me a lot of convenience when seeking information.
Risk
I feel safe when seeking information using this channel.
Information search on this channel involves higher risk compared to others.
Purchase
Quality
The products offered meet my expectations.
The products offered on this channel are exactly what I am looking for.
The products offered on this channel satisfy all my needs.
Convenience
Purchasing products on this channel requires little effort.
I am flexible about when I purchase products through this channel.
Risk
On this channel the likelihood of a wrong purchase is especially high.
On this channel I am especially likely to get a product purchase wrong.
Price
I might purchase products at an inflated price on this channel.
The prices offered on this channel are higher than on other channels.
Transaction
Convenience
The channel design eases the execution of transactions.
It is easy to conduct transactions on this channel.
I need only a little time to conduct transactions on this channel.
Risk
I feel safe when conducting transactions through this channel.
Price
The prices offered on this channel are higher than on other channels.
The fees for using this channel are higher than on other channels.

Curriculum Vitae

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Ehrenwörtliche Erklärung

Ich habe die vorgelegte Dissertation selbst verfasst und dabei nur die von mir angegebenen Quellen und Hilfsmittel benutzt. Alle Textstellen, die wörtlich oder sinngemäß aus veröffentlichten oder nicht veröffentlichten Schriften entnommen sind sowie alle Angaben, die auf mündlichen Auskünften beruhen, sind als solche kenntlich gemacht.

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